DISCUSSION PAPER SERIES

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ABSTRACT

Gimme Shelter. Social Distancing and Income Support in Times of Pandemic*

Strict containment limits the spread of pandemics but is difficult to achieve when people must continue to work to avoid poverty. A new role is emerging for income support: by enabling people to effectively stay home, it can produce substantial health externalities. We examine this issue using data on human mobility and poverty rates in 729 subnational regions of Africa, Latin America and Asia during the first year of COVID-19. We focus on within-country differential mobility changes between higher- and lower-poverty regions. Conditional on country-day fixed effects, shelter-in-place orders decrease work-related mobility significantly less in poorer regions. Emergency income support programs seem to help people to reduce their mobility on average, mitigating the poverty-driven gap in mobility between regions and, hence, regional differences in contagion rates.

JEL Classification: H12, I12, I18, I38, O15

Keywords: COVID-19, poverty, policy, lockdown, social protection, compliance, mobility

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1. Introduction

The COVID-19 pandemic has triggered unprecedented deployment of anti-contagion policies throughout the world, among which mobility restrictions feature prominently. By mid-April 2020, most countries implemented lockdown measures and virtually all schools in the world were closed.[1] While these confinement policies have contributed to curb the spread of the pandemic, over and beyond changes in behaviors that might have occurred naturally,[2] they have also triggered a major global economic crisis.[3] This unprecedented downturn has disproportionally hit the most vulnerable households, as shown in recent evidence using variation within country (e.g. Papageorge et al., 2020, Wright et al., 2020) or across countries (e.g. Adams-Prassl et al., 2020, Dang et al., 2020). These recent studies also hint to another critical consequence of lockdowns, namely the fact that the poorest could not afford to stay home. For the US, Papageorge et al. (2021) show that people with lower income and an inability to tele-work were less likely to engage in behaviors that limit the spread of the disease. This observation also applies to low- and middle-income countries: adherence to stay-at-home orders (SHO) is limited amongst poor households, who typically face acute food shortage and must seek out income generating activities on a daily basis. Thus, poverty is not only increased by the epidemic but can also contribute to fuel its growth.[4]

In this context, a new role has emerged for redistributive programs. Along with mobility restrictions, governments around the world have engaged in supplementary income support (IS) policies, expanding existing social transfers and/or setting up new ones.[5] According to Gentilini et al. (2020), at least $800 billion have been invested in social protection in 2020 (around 1% of global GDP), amounting to more than 1,400 measures, of which about one-third took the form of cash transfers reaching over 1.1 billion people. Initially motivated as a means of preserving livelihoods and avoiding sharp increases in extreme poverty, IS programs may have also helped poor populations comply with public health rules and thus contain COVID-19. Some of these programs are explicitly labelled in this way, for instance the 'Bogotá Solidaria en Casa' in Colombia, 'Quédate en Casa' in Dominican Republic, etc. Yet, to date, there is very little evidence about this effect, namely the extent to which IS helps reduce mobility, and hence generates positive health externalities, in a time of pandemic.

[1] See https://ourworldindata.org/ (notably `stay at home' and `school closure' graphs) for visual tracking of policy implementation over time.

[2] See e.g. Chinazzi et al. (2020), Kraemer et al. (2020), Hsiang et al. (2020), Koh et al. (2020), Flaxmans et al. (2020) and Aubert and Augeron-Véron (2021).

[3] ILO estimates that 1.6 billion workers in the informal economy were at risk of losing part or all of their livelihood (ILO, 2020). Reduced economic activity translated into large increases in poverty (e.g. Gutierez-Romero and Ahamed, 2020; Decerf et al., 2020; Sumner et al., 2020; Egger et al. 2021).

[4] Existing evidence focuses on geographically-specific cases, including Ghana, South Africa and Chile (Durizzo et al., 2021, Carlitz and Makhura, 2021, Bennett, 2021). A more global picture is provided in our preliminary work (Bargain and Aminjonov, 2021), yet focusing on 9 countries only.

[5] See for instance Imbert and Orkin (2020), Hanna and Olken (2020) and Alon et al. (2020) for early discussions on policy options in poor countries. Note also that optimal policy choices have been discussed since the onset of the pandemic in the face of the apparent trade-off between lives and livelihoods (Gourinchas, 2020).

In this article, we shed light on this issue, focusing on a large number of low- and middle-income countries. We examine the role of poverty on work-related mobility and investigate the cushioning effect of IS policies, i.e. how these programs facilitate compliance with mobility restrictions and, hence, slow down the spread of COVID-19. Our approach mobilizes several types of openly available data. First, we collect recent pre-pandemic estimates of poverty incidence for 729 subnational regions across 43 countries mainly in Africa and Latin America as well as a few countries in the Middle East and Asia. We classify individual regions as being of higher (lower) poverty incidence if their poverty headcount is above (below) the median of the country. Second, we merge this data with daily regional mobility estimates from Google COVID-19 Mobility Reports, over 202 days (February 15 – September 3, 2020). Third, we rely on the Oxford COVID-19 Government Response Tracker (OxCGRT, 2020), which records daily changes in state interventions during the COVID-19 pandemic. For each subnational region in our sample, we assign national-level changes in policies related to SHO and IS programs. We also use regional information on urban density, trust in government, mobile internet access and the count of COVID-19 cases.

Our preferred estimates rest on panel specifications in which changes in work mobility are related to indicators of SHO measures and IS policies. We control for country-time fixed effects to account for all possible time-varying confounders at country level, including local health conditions and how health policies daily interact with state capacities and population characteristics. While these country-day dummies also absorb the average effect of the daily policy mix (e.g. lockdowns with or without IS) in a country, we focus on the *heterogeneous* effect of these policies across higher- vs lower-poverty regions within countries. In particular, we seek to estimate how the poverty-related mobility differences across regions is mitigated when IS programs are activated.

Results first show that all regions greatly reduce workplace mobility in response to SHO, but the magnitude of the drop is on average significantly smaller in regions with higher incidence of poverty (i.e. 20% less than in other regions). We interpret this significant difference as a higher propensity to continue labor activities in poorer regions. This interpretation is consistent with the fact that this poverty gap in mobility is not found for essential trips such as going to the grocery/pharmacy. Importantly, when IS is provided in response to the pandemic, mobility decreases overall and more so in poorer areas (the mobility gap between higher and lower poverty regions drops to 7%). Since our findings highlight the importance of social assistance for the poor during a pandemic, not only in terms of securing livelihoods but also in reducing the risk of infection, we complete the analysis by examining the implications for the propagation of COVID-19. We combine the estimated poverty-elasticity of mobility with an estimate of the mobility-elasticity of virus diffusion. We find that IS policies have likely resulted in a slower spread of the virus through work-related mobility: switching from a lower- to a higher-poverty region within a country is associated with 51% more COVID-19 cases after five months when SHO operate without IS, whereas the poverty gap causes only 26% additional cases when IS is provided.

Beyond these results, we see several contributions from this research. We give strong support to the use of IS as part of the short-term policy response to a pandemic. In this way, we contribute to the existing literature on social protection in developing countries. Over the past two decades, IS policies have taken a predominant role in low-income countries,[6] many studies pointing to their ability to preserve a minimum standard of living for the poor, help protect their asset base in the face of a negative income shock and avoid long-term poverty traps (see the meta-analysis of Hidrobo et al, 2018). In comparison, fewer studies have investigated the effect of IS policies on aggregate welfare. The question is fundamental if one is to value the overall returns on investments in these policies.[7] The present study is among the first, to our knowledge, to examine the effect of IS policies on aggregate health outcomes in low- and middle-income countries in the context of a global pandemic. With the number of human infectious diseases constantly on the rise since the 1950s (Smith et al. 2014), our results offer further support to policies geared at protecting the income of the poor. Another contribution is to provide a 'big picture' of the role of IS, with global estimates that are complementary to the few existing studies focusing on specific policies in local contexts (for instance the health effect of a randomized cash transfer in Kenya, analyzed by Brooks et al., 2020, and Banerjee et al., 2020). Further work should attempt to connect both levels of analysis, possibly by using more disaggregated mobility data and providing more heterogeneous effects across contexts and policy types.

2. Data

In this section, we describe the four main types of data used in the analysis as well as data treatment and selection.[8]

2.1. Human Mobility during COVID-19 Pandemic

We use human mobility data from the Google Mobility Reports. The reports record daily changes in the number of visits to – or length of stay at – various locations before and during the COVID-19 pandemic. They are based on aggregated and anonymized data from users' (Android operated) mobile device location history. The locations are grouped in several categories including mobility to workplaces (our key variable of interest) and mobility to grocery and pharmacy (used in placebo checks). The Google measures take into account the fact that the person is not at home during these activities: this is a key aspect of our demonstration regarding work-mobility, since it reveals a tension between health-related risks (i.e. leaving the home and being exposed to the virus) and income-related risks (i.e. the ability to generate livelihood, whatever the nature of the job: formal or informal, agricultural or not,

[6] In 2011, the UK Department for International Development estimated that social transfers in low- and middle-income countries reached between 0.75 and 1 billion people. As of 2017, cash transfer policies were on-going in 149 countries in the World (World Bank, 2017).

[7] It has been argued that through reduced inequalities, increased social cohesion and enhanced human capital at the economy level, IS contributes to overall economic growth (Alderman and Yemtsov, 2014), generating positive spillovers (Angelucci and De Giorgi, 2009, Bobonis and Finan, 2009) and large fiscal multipliers (Egger et al., 2019).

[8] A synthetic description of the variables used is provided in **Table A1** in the Online Appendix.

etc.). For each type of mobility, daily measures are expressed relatively to the average level in a reference period of January 3 to February 6, 2020, normalized to 100 (see Google, 2020, for more details). The data regularly tracks mobility across more than 130 countries since February 15, 2020, but we focus on a subset of low- and middle-income countries for which mobility data is available at the subnational level. As a result, our sample covers a panel of 729 subnational regions across 43 countries in Africa, Latin America, Middle East and Asia, observed for 202 days from February 15 to September 3, 2020.[9]

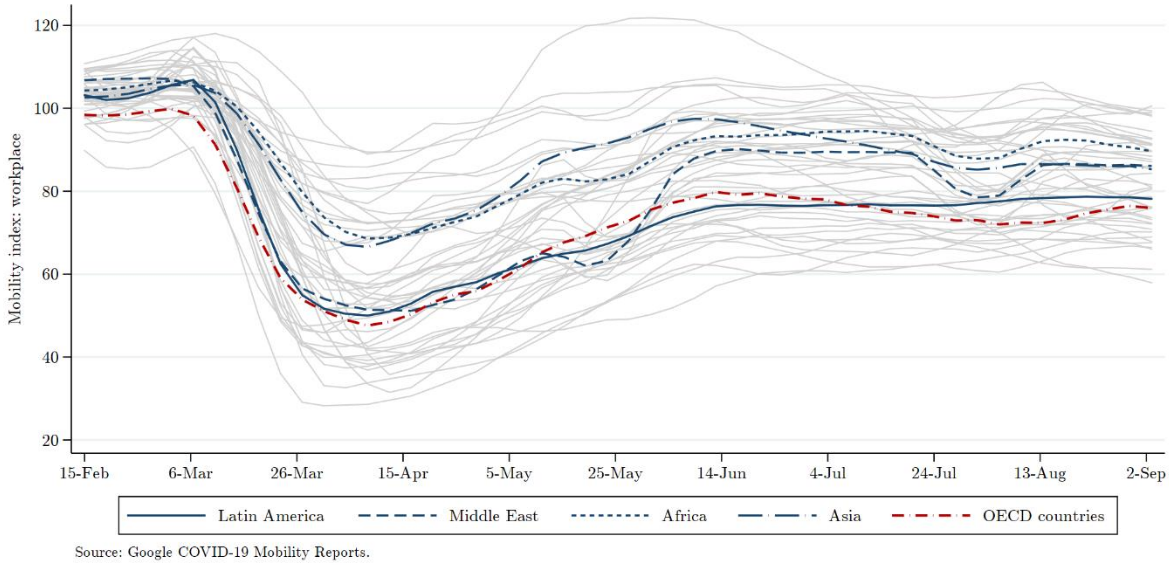


Figure 1. National Trends in Work-related Mobility.

Figure 1 illustrates the time trends of work-related mobility using national averages for all the countries in our sample (solid grey lines) as well as the summary trends for broad geographical groups of low- and middle-income countries (blue lines) and high-income countries (red line). The horizontal axis reflects our time coverage. The vertical axis represents the level of work mobility in reference to the value 100 for the reference period. For most of the countries, we observe work-related mobility levels that are very close to this benchmark in February-early March 2020, but a sharp drop in mobility in late March, which corresponds to the first round of physical distancing measures taken by most governments around the world in response to the rapid spread of COVID-19. While the rates of change vary substantially across countries, it is striking to see that mobility restriction measures were implemented almost simultaneously at a global level and in particular in low- and middle-income country - for the latter, this response seems to be more influenced by the spread of COVID-19 in Europe and North America than to the actual local state of the epidemic. As for the disparities in mobility responses in our sample, it may be due to local policy stringency or different information about (and perception of) the risks, but also to other factors affecting behavioral responses such as poverty – our heterogeneity of interest in this paper. For instance,

[9] The list of countries is reported in **Figure 2(b)**.

as depicted in **Figure 1**, the decline in work-related mobility was on average more pronounced in richer countries (OECD, Latin America or the Middle East) than in poorer regions of the world (Africa and Asia). We will follow this line of reasoning and exploit differences in poverty, but at the regional level within countries, in what follows.

2.2. Poverty

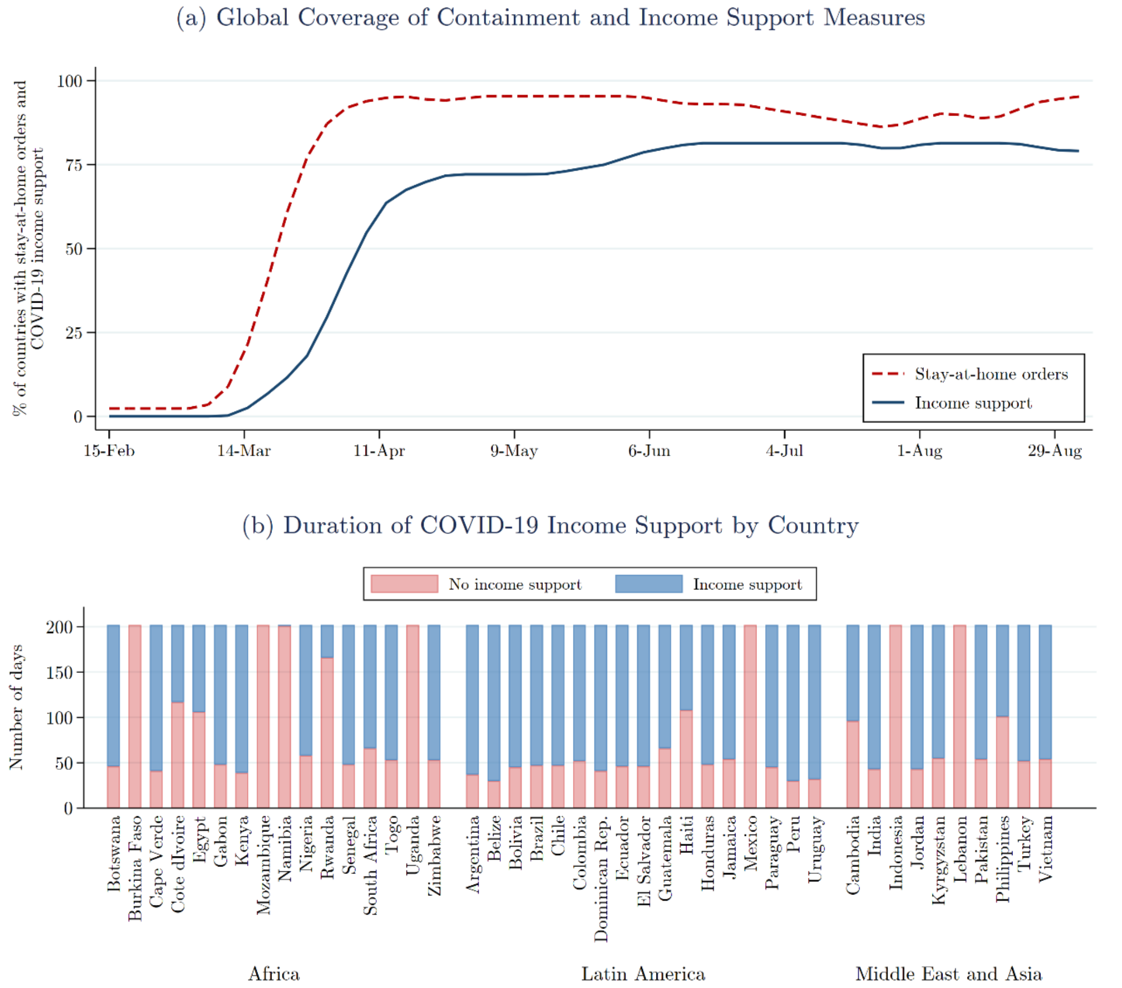
We measure poverty at the level of subnational regions using pre-pandemic poverty headcount ratios, i.e. the share of people in the region living below the poverty line. To cover as many countries as possible, we use the latest official poverty statistics, when provided at regional level, or our own poverty calculations based on recent household surveys. Regional poverty rates are calculated using per capita income or consumption and, for poverty lines, the standard World Bank international lines or national definitions based on the value of a basic bundle of goods.[10] To make interpretation easier, we use a binary measure of poverty hereafter, i.e. a dummy indicating if the regional poverty headcount ratio is above (`higher-poverty') or below (`lower-poverty') the country-specific median.

2.3. Policy Information

Containment Policies. We exploit data from OxCGRT (2020), which records daily changes in national non-pharmaceutical interventions during the pandemic. Our main containment variable is a binary indicator of whether governments have enacted any SHO, either as requirement or recommendation, or not.[11] In all the countries of our sample, SHO were imposed at some point during the period February 15-September 3, with an average duration of 155 days in total over the period. The daily variation in the proportion of countries enforcing SHO is represented in **Figure 2(a).**

Income Support. Our key measure, also drawn from OxCGRT (2020), is an indicator tracking whether governments provide IS in form of direct in-cash/in-kind payments to those who lost their jobs or were not able to work due to the pandemic. Thus, importantly, we focus only on "new" transfers introduced in response to the COVID-19 pandemic: they may come as a completely new program, as increased benefits for current recipients (vertical expansion) or as an extension of existing programs towards new beneficiaries (horizontal expansion). In our estimation, we use a binary definition, i.e. whether any transfer was provided or not for a given country-day. The variable is zero at the onset of the pandemic crisis (in February and early March 2020). We see the daily variation in the proportion of countries with an active IS program in **Figure 2(a)**. In our sample, 37 out of 43 countries (86%) introduced IS programs during February 15 – September 3, for 120 days on average. **Figure 2(b)** shows which countries have done so and for which duration.

[10] A detailed description of sources of poverty data or household data used to calculate regional poverty is provided in **Table A2** in the online appendix.
[11] Additional results using SHO stringency levels are available from the authors but not changing our main message. See **Online Appendix B** for an overview of these results.



Source: author's calculations based on OxCGRT data on COVID-19 containment policies and income support. Graph (a) is based on local polynomial fit of the daily share of countries with national stay-at-home orders and COVID-19 income support. Stay-at-home orders indicate the daily status of whether government imposes any stay-at-home orders as recommendations or requirements (country-day variation in stay-at-home orders). COVID-19 income support shows the daily status of whether government provides any income support to those who cannot work or lost their job due to the COVID-19 pandemic (country-day variation in income support). Low (high) income support indicates the period in which income support covers less (more) than 50% of income lost due to the COVID-19 pandemic.

Figure 2. Policy Global Coverage and Income Support duration by Country

2.4. Additional Data

Mobile Internet Access. Google mobility data is based on Google Location History (GLH) in users' mobile devices. Android devices are increasingly popular in low- and middle-income settings as an affordable way to access the internet. According to the Pew Research Center (2019), the average smartphone ownership rate in 2018 was around 45% in emerging economies (76% in advanced economies) with a rate of cellular subscriptions that has reached an average of 115 per 100 people. Yet, mobile internet might predominantly concern wealthier areas, where more people can afford smartphones (Ballivian et al., 2016). Even in this case, the effect of poverty on mobility may represent an interesting lower bound of the true effect if GLH information captures the mobility of the least poor within poorer regions, i.e. those who could reduce their mobility the most. To investigate this point further, we shall exploit two surveys, the Latinobarometer and the Afrobarometer, in which respondents are asked whether they own a smartphone or a mobile phone with internet. We calculate a dummy variable taking the value 1 if the share of survey respondents with mobile internet access is above the country-level median.

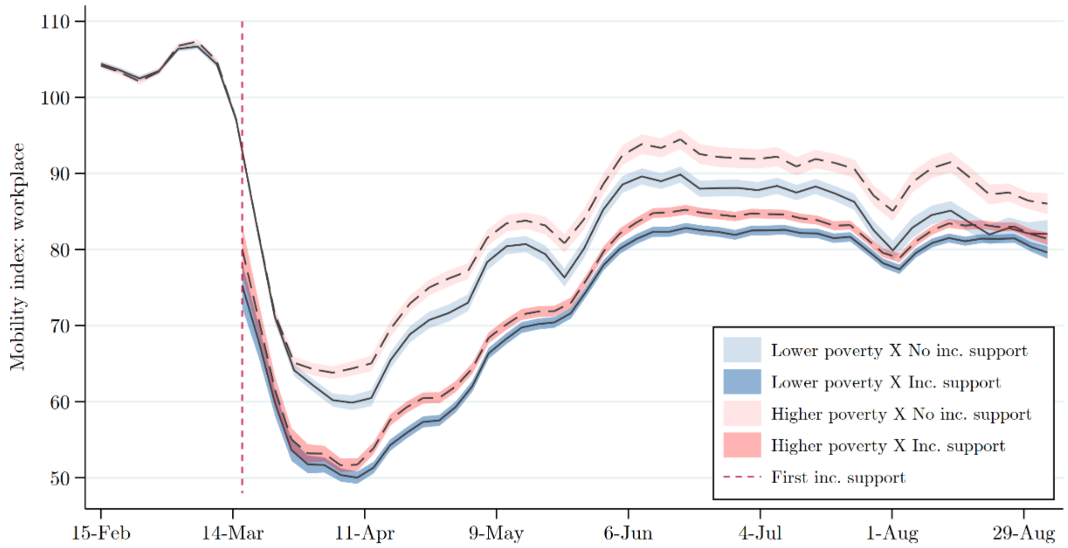
Population Density and Trust in Government. Poverty is often associated with the level of population density. Hence, as a sensitivity check, we mobilize the database 'Gridded Population of the World' by the CIESIN of Columbia University. The data records population count for 30 arc-second (about 1km on average) grid cells. While each subnational region has a varying number of cells, we use the average population count per cell in a given region. We split subnational regions into higher- and lower-population density groups based on whether regional density is above or below country-specific median level. Additionally, we test whether the effect of poverty and IS on mobility varies with the trust in government. We exploit data from the Afrobarometer, Latinobarometer and Arabarometer to measure regional level of trust in government before the pandemic. In each of the barometers, respondents were asked to rank their level of trust on a 0-4 scale (from "no trust" to "a lot of trust"). We calculate regional-level average of reported trust and allocate regions into lower- and higher-trust groups within countries using country-level median as a cutoff.

COVID-19 Cases. Finally, we study the implications of our results for the spread of the virus, which requires the estimation of mobility-elasticity of virus growth. For that, we use data from the European Center for Disease and Control (ECDC), which provides information on daily cases of COVID-19 across the sampled countries.

3. Graphical Evidence

Using these datasets, we first aim to measure the extent to which higher-poverty regions responded differently to SHO policies than lower-poverty ones, then investigate whether IS could help mitigate the adverse effect of poverty on individuals' capacity to reduce their exposure to the virus. We start with a graphical analysis of mobility patterns across subnational regions by local level of poverty.

Figure 3 depicts the daily average regional mobility to workplace for the period of February 15 – September 3, 2020, differentiating regional mobility patterns by pre-pandemic poverty incidence level and daily IS status. We use all regions in our sample and a local polynomial fit with its 95% confidence interval (CI). Let us focus first on the average mobility of country-day cells without IS, the CI of which is depicted in light pink (blue) for lower (higher) poverty regions. Mobility fluctuates around 100 in late February and early March, i.e. around the same level as in the reference period. Around mid-March, many governments started to call for physical distancing, leading to the sharp drop in work-related mobility also illustrated in **Figure 1**. Before mid-March, SHO had not yet been implemented: lower-poverty and higher-poverty regions exhibit very similar trends. By the end of March 2020, most countries in our sample had enacted SHO: mobility reaches a low peak at that time. After SHO are put in place, a marked difference appears between regions: those with lower poverty reduce mobility significantly more than higher-poverty regions. These results support the idea that poverty leads people out of their home to secure daily livelihoods despite the contamination risks. This poverty-related mobility gap appears to be even slightly larger at the end of the period, when harsh economic conditions make it difficult for anyone - but perhaps more so for the poorest - to stay at home.



Source: author's calculations based on Google mobility data (mobility for workplace), poverty data from national statistics offices and authors' estimations using household surveys, and OxCGRT data on COVID-19 income support. Local polynomial fit with 95% CI of daily mobility across regions, weighted by (1/# of regions in the corresponding country). Poverty is measured as the share of people living below national or international poverty lines in a subnational region. Poverty is defined as lower (higher) if region's poverty rate is below (above) country's median regional poverty rate. COVID-19 income support shows the daily status of whether government provides any income support to those who cannot work or lost their job due to the COVID-19 pandemic (country-day variation in income support). Low (high) income support indicates the period in which income support covers less (more) than 50% of income lost due to the COVID-19 pandemic.

Figure 3. Work-related Mobility by Regional Poverty Levels with and without Income Support

Poverty hence undermines the efficacy of containment policies – or more generally the ability for people to self-isolate – but can be counteracted by IS programs such as those launched in Spring 2020. Many governments have introduced new or additional social protection programs to help people cope with lockdowns and income losses. As explained, we use the OxCGRT indicator, which records IS introduced in response to the COVID-19 pandemic either as a new program or as an extension of existing schemes. COVID-19 IS programs begin on March 16th (in Belize and Peru) and by mid-April, around 70% of the countries have a specific transfer in place. **Figure 3** represents average mobility levels in presence of IS, starting from March 16th, for higher- (dark pink) and lower-poverty (dark blue) regions. This leads to the central results of this study. First, upon provision of IS, the level of mobility shifts downwards for both types of regions: pandemic-related IS schemes have seemingly helped improve compliance with containment rules and reduce work-place mobility. Second, the impact seems larger among higher-poverty regions: the difference between lower- and higher-poverty regions is larger in the absence of IS (light blue vs light pink) than when IS is in place (dark blue vs dark pink), and the difference tends to disappear in the latter case. This finding hints towards the health externalities of social protection for poor people who have to continue work-related mobility to maintain livelihoods during the pandemic. The rest of the paper aims to test this result while accounting for country-level unobserved confounders.

4. Estimations

4.1 Empirical Approach

Our empirical strategy does not aim to explain the role of SHO and IS on mobility patterns overall, since country-specific mobility trends are affected by many time-varying confounders. Our analysis focuses exclusively on the within-country heterogeneity between higher- and lower-poverty regions, with regional poverty being defined relatively to the country-specific median. We select only country-day cells for which the policy mix is as follows: no policy, SHO only or both SHO and IS.[12] Mobility in a subnational region i of country c on day t is written:

$$Mobility_{ict} = \alpha + \beta Poverty_i \times SHO_{ct} + \gamma Poverty_i \times SHO_{ct} \times IS_{ct} + \theta_{ct} + \mu_i + \varepsilon_{it} \quad (1)$$

For $Poverty_i$, we rely on the binary measure of regional poverty incidence before the pandemic, i.e. taking the value of one if regional poverty rate is above the country median (higher poverty) and zero otherwise (lower poverty). Our baseline indicator to define lockdown (income support) periods, SHO_{ct} (IS_{ct}), is a dummy variable equal to one if SHO (IS programs) are enforced in country c on day t. All time-varying confounders are captured in country-day fixed effect θ_{ct}.[13] The policy mix for country c on day t is also absorbed by these FE, but this is not an issue since we focus only on the relative effect in poorer region. Comparing periods without and with SHO identifies coefficient β, i.e. the poverty gap in mobility when only SHO are in place. Comparing SHO periods without and with IS identifies coefficient γ, i.e. the additional shift in the mobility poverty gap caused by the introduction of IS.[14] We control in vector μ_i for the regional poverty status $Poverty_i$ and additional regional characteristics such as population density and trust (the latter variables will also be interacted with SHO or IS dummies in robustness checks in order to test alternative mechanisms beyond the work-related interpretation of the poverty gap). We cluster standards errors at the country level over time to address both autocorrelation and the correlation of error terms across regions within countries (i.e. at the level of policy decisions).[15] We also reweight each observation by the inverse of the number of subnational regions in the corresponding country, in order to avoid over-representation of a country with numerous regions.

[12] Note that we ignore here and in our application the few days during which SHO are lifted while IS is still operational (5.1% of the period).

[13] They possibly include country-specific trends in the pandemic, in the economic situation, in citizens' awareness about the virus, in SHO enforcement ability and health service capacities (in relation with state capacities), etc.

[14] Online **appendix B** illustrates the identification strategy in more detail by decomposing the periods.

[15] Results are very similar when standard errors are cluster-bootstrapped at regional level (1000 replications).

4.2 Main Results

Our main results are reported in **Table 1**. In the first row, the coefficient on poverty is rarely significant, indicating that the (within-country) initial mobility difference between higher- and lower-poverty regions was marginal. Column (i) shows results for a model where regional controls μ_i include only the poverty status (similar results are obtained when using the continuous regional poverty rate). According to the estimate of β in the second row, poorer regions experience a smaller reduction in mobility than higher-poverty regions during SHO periods. The differential of 5.2 represents around 20% of the average drop in mobility (i.e. 25.8 points on our 0-100 scale) among lower-poverty regions between the pre-lockdown period and the days with SHO.

Dep. Var.: Mobility to Workplace	All countries		Africa	Latin America	Middle East & Asia	Low & lower-middle income	Upper-middle income
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Poverty	0.574*	-0.252	0.877	0.664	0.039	0.491	0.668
	(0.317)	(0.511)	(0.527)	(0.545)	(0.614)	(0.448)	(0.460)
Poverty X Stay-at-Home	5.167***	5.538***	6.436***	1.273**	6.466*	5.544***	4.699**
	(1.166)	(1.312)	(1.239)	(0.451)	(2.955)	(1.303)	(2.088)
Poverty X Stay-at-Home X Income Support	-3.320**	-3.348**	-4.109**	0.350	-4.754	-4.588***	-2.118
	(1.283)	(1.542)	(1.650)	(1.111)	(2.915)	(1.247)	(2.376)
R-squared	0.841	0.899	0.834	0.883	0.733	0.802	0.880
Observations	132,639	68,615	35,163	60,214	37,262	61,272	71,367
Country X Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region reweighting	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	No	No	No	No

Source: authors' estimation using Google reports for workplace mobility, regional poverty rates (from national statistics or authors' estimations) and information on COVID-19 policy response from OxCGRT for the period February 15-September 3, 2020. Poverty is defined as lower (higher) if region's poverty rate is below (above) country median poverty rate. Stay-at-Home indicates the period in which national stay-at-home orders, either recommendations or requirements, are imposed. Income support indicates the period in which government provides income support to those who cannot work or lost their job due to the COVID-19 pandemic. Days when stay-at-home orders are lifted, following the first lockdown, are excluded. Regional control variables include mobile internet access rate, regional population density (in log) and average regional score for trust in government (in log). Region reweighting: observations are weighted by 1 over the # of regions in the corresponding country. Standard errors clustered at country level in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 1. Effect of Stay-at-Home Orders and Income Support on the Differential Workplace Mobility of Poorer Regions

The third row reports the estimate of γ. It shows that the poverty gap in mobility is reduced by 3.3 points when IS are in place, falling to 1.85 points only, or 7.2% of the average mobility drop in lower-poverty areas. Results are confirmed when adding further regional controls, namely mobile internet access, population density and trust, in column (ii), even though the sample size is reduced by around half in this case. The rest of the table reports estimates for specific geographic areas. The within-country poverty gap is present everywhere but stronger on the African and Asian continents (cf. columns iii-v); consistently, it is larger in poorer countries (cf. columns vi-vii). The IS reducing effect is also large and significant in these countries, yet it is null in Latin America, which conveys that there is much less within-country behavioral differences in this area.

Note that OxCGRT (2020) reports information on IS levels, with high/low IS corresponding to transfers that cover more/less than half of the earnings losses due to the pandemic. We use this information instead of the binary IS for the only two countries in the sample that switched from low to high IS over the period (Chile and Uruguay). We find that more mobility reduction is achieved with higher IS levels. Even if the exploitable time switch for causal inference is available for two countries only, this additional result supports our main interpretation that IS helps reduce the mobility poverty gap.[16]

4.3 Robustness Checks

Non-work-related Mobility as Placebo. Previous results are consistent with the conjecture that work-related mobility was less reduced among poor people because of the urgency to make ends meet. As a placebo test, we verify that the poverty gap is less pronounced when other types of mobility are considered. **Table 2** reproduces baseline result in column (i). It also shows estimate for essential activities in (ii), using Google data on mobility to grocery/pharmacy. In this case, the mobility gap between regions is insignificant, supporting the assumption that non-compliance with mobility restrictions is mostly associated with work-related activities for the poorest.

	Mobility Types		Heterogenous Effects (Work Place Mobility)					
	Workplace	Grocery & Pharmacy	Mobile Internet Access		Population Density		Trust in Government	
			Low	High	Low	High	Low	High
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Poverty	-0.252	-0.390	-1.559**	2.692***	-2.284***	2.745***	1.748**	-0.836
	(0.511)	(0.720)	(0.745)	(0.624)	(0.824)	(0.646)	(0.635)	(0.935)
Poverty X Stay-at-Home	5.538***	1.066	4.566***	5.225**	5.897***	3.906***	6.617***	5.826***
	(1.312)	(1.152)	(1.021)	(2.182)	(1.055)	(1.310)	(1.908)	(1.313)
Poverty X Stay-at-Home X Income Support	-3.348**	0.714	-2.350*	-4.749*	-3.208**	-3.121**	-5.005**	-3.546**
	(1.542)	(1.816)	(1.335)	(2.706)	(1.252)	(1.507)	(2.119)	(1.638)
R-squared	0.899	0.857	0.890		0.847		0.885	
Observations	68,615	51,882	69,955		132,639		77,515	
Country X Day FE	Yes	Yes	Yes		Yes		Yes	
Region reweighting	Yes	Yes	Yes		Yes		Yes	
Controls	Yes	Yes	Yes		Yes		Yes	

Source: authors' estimation using Google reports for workplace mobility, regional poverty rates (from national statistics or authors' estimations) and the information on COVID-19 policy response from OxCGRT for the period February 15-September 3, 2020. Poverty is defined as lower (higher) if region's poverty rate is below (above) country median poverty rate. Stay-at-Home indicates the period in which national stay-at-home orders (recommendations or requirements) are imposed. Income support indicates the period in which government provides income support to those who cannot work or lost their job due to the COVID-19 pandemic. Days when stay-at-home orders are lifted, following the first lockdown, are excluded. For columns (i)-(ii), regional control variables include mobile internet access rate, regional population density (in log) and average regional score for trust in government (in log). For columns (iii)-(viii), not to loose too many observations, we limit the set of controls to the heterogeneity of interest (e.g. for results with heterogeneous effects by level of mobile internet access, we include a dummy for a lower level of mobile internet access rate). Region reweighting: observations are weighted by 1 over the # of regions in the corresponding country. Standard errors clustered at country level in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 2. Effect of Stay-at-Home Orders and Income Support on the Differential Workplace Mobility of Poorer Regions: Checks

Mobile Internet Access. Using Google mobility reports in the context of poverty analysis raises a question of population representativeness. If the poorest within poor regions have the least access to mobile internet and are, at the same time, the least able to stay at home, our approach underestimates the effect of poverty on mobility. As a robustness check, we rerun our estimations to capture heterogeneous effects *between higher-poverty regions* depending on their level of mobile internet access (defined as above vs. below median mobile internet access rates). **Table 2** (columns iii-iv) shows that our main results hold in both types of poor regions,

[16] See more details in online **appendix B.**

indicating that varying the degree of representativity does not alter our conclusions much. Note that this is reassuring but only suggestive since this check is based on a subset of countries for which mobile internet information is available (374 subnational regions across 27 countries in Africa and Latin America).

Alternative Mechanisms: Population Density and Trust. We explore potential confounders. We start with population density measured as a binary variable. If poorer regions are also rural, our results may be affected by other mechanisms including regional specificities in terms of labor market activities or urban/rural differences in mobile internet coverage. **Table 2** (columns v-vi) shows that the poverty gap in mobility is present and significant during SHO for both lower and higher levels of population density (although slightly smaller in urban areas). The effect of IS is similar for both groups and comparable to baseline estimates. Another potential mechanism is the confidence in governments, which may affect our results if it is correlated with poverty. Several papers have documented that lower trust is associated with a lower degree of adherence to containment measures in the context of the COVID-19 pandemic (Bargain and Aminjonov, 2020; Brodeur et al. 2021). **Table 2** (columns vii-viii) points again to consistent results when differentiating poorer regions by level of trust in government. For both higher- and lower-trust levels, we find significant poverty gaps in mobility during SHO period. The correction effect of IS in poor regions with low trust is larger than the baseline estimate, which might signal another positive externality of IS, i.e. the ability to "compensate" for lower trust in government in the poorer regions.

Discussion. There might be other mechanisms that we do not cover in this sensitivity analysis, such as within-country differences in local capacities (to enforce mobility restrictions or provide transfers) that may be related to poverty differences. In that sense, our evidence is suggestive. Note however that the problem of time-varying confounders would be more acute if we compared regions of the world (rather than regions within countries). This was the approach followed in a previous version of this paper (Aminjonov et al., 2021), now reported in the online **appendix C**. An alternative definition of poverty is used there (i.e. according to the global median of regional poverty) and country-day effects are not introduced, so that both between- and within-country variation is used. Notwithstanding, results convey the same message: the poverty gap is significant during lockdowns (characterizing work-related mobility specifically) while IS reduces this gap significantly. It means that the pattern emphasized in the present paper is pervasive and found at different levels: when comparing regions within countries or when comparing countries or groups of countries by poverty levels.

4.4. Implications for the Spread of COVID-19

Lastly, we provide back-of-the envelope estimates of how the poverty gap in mobility during SHO, and the dampening effect of IS, reflect on the spread of COVID-19 through the mobility channel. First, we calculate the poverty gap in mobility during SHO period, and the effect of IS, as the percentage deviations from mean mobility in the corresponding periods, using our baseline estimates from Table 1. We find that the gap of 5.2 mobility points corresponds to a

6.9% deviation from mean mobility (during SHO days without IS). Similarly, the effect of IS (-3.3 points) corresponds to a -4.4% deviation from mean mobility (during SHO with IS days).

In the second step, we estimate a mobility-elasticity of the growth in COVID-19 cases using country-level data on COVID-19 cases. We calculate the upcoming growth rate of COVID-19 cases by comparing the daily cumulative number of cases to that of two weeks ahead and divide the rate of change by 14 to obtain a daily average growth rate (the two-week lag is used to account for the average known duration between infection and public report). Then, we regress the growth rate on country-level mobility index, day dummies, country fixed effects and additional controls, separately for SHO days without and with IS. Estimates yield elasticities of 1.2 and 0.8 respectively, that is, a 10% increase in mobility leads to 12 % and 8% increases in the upcoming growth rate of COVID-19 cases respectively.[17]

Finally, we combine both types of elasticities. For SHO days, we find a combined elasticity of 8.3 (6.9 x 1.2), i.e. the within-country poverty gap in mobility is associated with a 8.3% higher growth rate of COVID-19 cases. When IS is enacted on top of SHO, this elasticity is reduced by 3.5 percentage points (4.4 x 0.8) and drops to 4.8%. We can provide an illustration of the magnitude of these effects. According to official figures, the *average* number of cumulative cases in our sample of 43 countries passed the threshold of 100 around March 20, reaching 4,600 cases after two months (mid-May) and 256,000 cases after five months (mid-August). Based on our estimated elasticities, the poverty gap in mobility between lower- and higher-poverty regions within a country would be associated with around 132,000 additional cases after five months if SHO were implemented without IS. With IS schemes in place, this poverty gap in terms of virus spread would be reduced to 68,000 cases (i.e. 48% fewer additional cases). We also run similar estimations using a continuous measure of poverty and find that a one standard deviation higher regional poverty rate, within country, would be associated to 85,000 more cases during SHO periods without IS and to 55,000 additional cases only when IS operates (i.e. 35% fewer additional cases).

4. Conclusion

The spread of COVID-19 and consequent restrictions on economic activity through containment policies pose a serious threat to the livelihoods of many of the most vulnerable households in the world. Governments have responded to this with an unprecedented expansion of their social protection programs and new transfers. Relative to pre-COVID levels, benefits have nearly doubled and coverage has grown by 240% on average (Gentilini et al., 2020). Admittedly, government assistance has been insufficient to sustain pre-crisis living standards and to prevent a sharp increase in food insecurity (Egger et al., 2021). Nevertheless, emergency support provided in response to the COVID-19 pandemic may have substantially helped to reduce the exposure of the poor to the virus.

[17] We calculate the elasticity as a one percent deviation from the mean mobility. That is, we first multiply estimates by the mean mobility and divide by the mean daily growth rate of COVID-19. Our mobility-elasticity of cases growth are of a comparable order of magnitude as the recent literature (e.g. Soucy et al., 2020).

We support this claim with new evidence exploiting spatial and time variation in human mobility across 729 regions of low- and middle-income countries. Regions with a higher incidence of poverty before the pandemic are concerned by a significantly lower reduction in work-related mobility, which we interpret as a lower ability to self-protect and comply with containment rules. Income support programs provide strong mitigating effects, allowing all regions to reduce mobility further but more so in poorer region, so the poverty gap in mobility partly disappears and the relative propensity of the poor to avoid infection increases. This conclusion stems from our global estimates but also from specific results for Africa, Asia and low/middle income countries.

Our findings strongly reinforce the idea that poorer and more vulnerable groups should be immediately targeted by substantial transfers in times of pandemic, as they allow governments to minimize the adverse welfare effects of containment policies and, critically, to maintain a higher level of adherence to these policies in poorer regions. We quantify the positive health externalities of income assistance programs and show that they reduce the impact of poverty on the spread of the virus by a third to a half on average.

Further research should provide more fine-grained information on policy options and their relative effectiveness (see detailed policy strategies in Gerard et al. 2020). This includes how the nature of the transfers, and in particular cash versus in-kind benefits, affects livelihoods and health externalities during a pandemic. The mode of targeting could also be further explored, for instance the quality of pre-pandemic targeting strategies versus new proxy-mean tests or community-based targeting (McBride and Nichols, 2018), the use of universal transfers versus the horizontal scaling up of existing schemes (such as temporary removals of the conditionality of some CCT) or innovative ways to reach informal workers (Carranza et al., 2020).

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Online Appendix

A. Descriptive Statistics

Variable	Type	Level of Measurement	Description/Values	Source
Mobility Index: Workplace / Grocery & Pharmacy	Continuous	Regional	An index measuring daily changes in the number of visits or time spent at workplace / groceries or pharmacies. Measured on (0-100) scale, with 100 as the baseline or pre-pandemic level.	Google COVID-19 Mobility Reports
Poverty	Binary	Regional	A dummy variable taking the value 1 if regional poverty headcount ratio is above the global median of regional poverty rates.	Official poverty statistics, authors' calculations using household surveys
Poverty Headcount Ratio / Standardized Poverty Rate	Continuous	Regional	Share of regional population living below international or national poverty lines. Value range [0-100] / Poverty Headcount Ratio standardized with respect to its global mean and standard deviation.	Official poverty statistics, authors' calculations using household surveys
Stay-at-Home Orders	Binary	National	A dummy variable measuring daily changes in stay-at-home orders (recommendations or requirements) during the COVID-19 pandemic and taking the value 1 if stay-at-home orders are enforced.	OxCGRT, Hale et al. (2020)
Income Support	Binary	National	A dummy variable measuring daily changes in income support provided to those who lost their jobs or cannot work due to the COVID-19 pandemic and taking the value 1 if income support is provided.	OxCGRT, Hale et al. (2020)
Cumulative number of COVID-19 cases	Continuous	National	A variable measuring daily changes in the number of cumulative reported COVID-19 cases.	European Center for Disease Prevention and Control
Mobile Internet Access	Binary	Regional	A dummy variable taking the value 1 if the share of survey respondents who own a smartphone or a mobile phone with internet access is above the country-specific median.	Afrobarometer 2019, Latinobarometer 2018
Population Density	Binary	Regional	A dummy variable taking the value 1 if regional population density is above the country-specific median.	Center for International Earth Science Information Network (CIESIN), Columbia University
Trust	Binary	Regional	A dummy variable taking the value 1 if the regional-level average trust score is above the country-specific median.	Afrobarometer 2019, Latinobarometer 2018, and Arabarometer

Table A1. Variable Descriptions

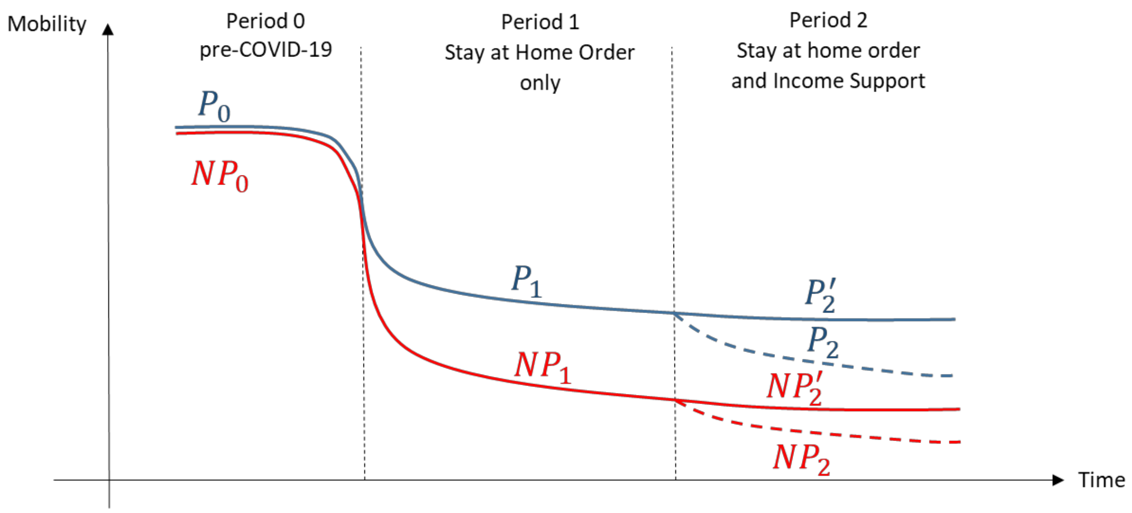
Country	Poverty Line*	Welfare Measure**	Data Source / Institute	Web-link / Web-page (report title)
Argentina	17.1	per capita income	Permanent Household Survey (EPH), 2019 / National Institute of Statistics and Census of Argentina (INDEC)	https://www.indec.gob.ar (Condiciones de vida Vol. 4, n° 4)
Belize	9.3	per capita consumption	Living Standard Measurements Survey, 2009 / Government of Belize and the Caribbean Development Bank, 2009	http://sib.org.bz/ (Country Poverty Assessment Report)
Bolivia	7.6	per capita income	Encuesta de Hogares, 2018 / National Institute of Statistics of Bolivia (INE)	https://www.ine.gob.bo (Pobreza y Desigualdad)
Botswana	2.2	per capita consumption	Botswana Multitopic Household Survey, 2015/2016 / Statistics Botswana	http://www.statsbots.org.bw (Poverty Stats Brief)
Brazil	5.5	per capita income	Continuous National Household Survey (PNAD Contínua), 2018 / Brazilian Institute of Geography and Statistics (IBGE)	https://www.ibge.gov.br/estatisticas/ (Sintese de Indicadores Sociais 2019)
Burkina Faso	1.8	per capita consumption	Enquête multisectorielle continue (EMC), 2014 / National Institute of Statistics and Demography (INSD)	http://www.insd.bf/ (Profil de pauvreté et d'inégalités)
Cambodia	2.5	indirect poverty estimation	The Commune Database Predictive Poverty, 2012 / Asian Development Bank, Ministry of Planning and United Nations Development Programme	https://www.adb.org/ (Country Poverty Analysis 2014)
Cape Verde	4.6	per capita consumption	III Inquerito as Despesas e Receitas Familiares, 2015 / Departamento das Estatisticas Demograficas e Sociais	http://ine.cv (Tables do Perfil da Pobreza)
Chile	11.6	per capita income	Encuesta Casen, 2017 / Ministerio de Desarrollo Social	http://www.desarrollosocialyfamilia.gob.cl/ (Informe Desarrollo Social 2019)
Colombia	5.3	per capita income	Integrated Household Survey (GEIH), 2018 / National Administrative Department of Statistics (DANE)	https://www.dane.gov.co/ (Condiciones vida, pobreza monetaria 18 departamentos)
Côte d'Ivoire	2.9	per capita consumption	Enquête sur le Niveau de Vie des Ménages, 2015 / Institut National de la Statistique de Côte d'Ivoire	http://www.ins.ci/ (Profil de pauvrete)
Dominican Republic	6.5	per capita income	Encuesta Nacional Continua de Fuerza de Trabajo (ENCFT), 2019 / Ministerio de Economía, Planificación y Desarrollo (MEPYD), Oficina Nacional de Estadística (ONE)	https://mepyd.gob.do (Boletín de estadísticas oficiales de pobreza monetaria en la República Dominicana año 5, no 7)
Ecuador	4.7	per capita consumption	Encuesta de Condiciones de Vida, 2013/2014 / Instituto de Estadistica y Censos (INEC)	https://www.ecuadorencifras.gob.ec
Egypt	6.6	per capita consumption	Household Income, Expenditure and Consumption Survey (HIECS), 2015 / Central Agency for Public Mobilization and Statistics (CAPMAS)	https://www.capmas.gov.eg (Regional poverty calculated by El-Haity and Armanious (2018) based (HIECS))
El Salvador	5.1	per capita income	Encuesta de Hogares de Propósitos Múltiples (EHPM), 2018 / Dirección General de Estadística y Censos (DIGESTYC)	http://www.digestyc.gob.sv/ (Principales Resultados de la Encuesta de Hogares de Propositos Multiples)
Gabon	5.7	per capita consumption	Enquête Gabonaise pour l'Évaluation de la Pauvreté 2, 2017 / Direction Générale de la Statistique	https://www.statgabon.ga/ (Gabon : Profil de Pauvreté 2017)
Guatemala	6.4	per capita consumption	Encuesta Nacional de Condiciones de Vida, 2014 / Instituto Nacional de Estadística	https://www.ine.gob.gt/ (Encuesta Nacional de Condiciones de Vida 2014: Principales resultados)
Haiti	3.7	per capita consumption	Enquête Sur les Conditions de Vie des Ménages Après le Séisme (ECVMAS), 2012 / The World Bank, Observatoire National de la Pauvreté et de l'Exclusion Sociale (ONPES)	https://www.worldbank.org/ (Investing in people to fight poverty in Haiti: Reflections for evidence-based policy making, World Bank Report)
Honduras	4.9	per capita income	Encuesta Permanente de Hogares de Propósitos Múltiples, 2018 / Instituto Nacional de Estadística	https://www.ine.gob.hn (Pobreza Monetaria)
India	2	per capita consumption	SDG dashboard/NITI Aayog (Tendulkar Committee Estimates), 2012 / National Institution for Transforming India (NITI Aayog)	https://niti.gov.in/state-statistics https://sdgindiaindex.niti.gov.in (SDG Poverty Statistics)
Indonesia	2.7	per capita consumption	National Socioeconomic Survey - Survei Sosial Ekonomi Nasional (Susenas), 2019 / Badan Pusat Statistik / Statistics Indonesia	https://www.bps.go.id (Poverty Statistics)
Jamaica	5.8	per capita consumption	Jamaica Survey of Living Conditions, 2012 / Statistical Institute of Jamaica (STATIN)	https://statinja.gov.jm/ (Mapping Poverty Indicators, Consumption Based Poverty in Jamaica)
Jordan	7.1	per capita consumption	Household Income and Expenditure Survey, 2010 / United Nations Development Program (UNDP), Jordan Department of Statistics (DOS)	https://www.undp.org/ (Jordan Poverty Reduction Strategy Final Report 2013)
Kenya	3.2	per capita consumption	Kenya Integrated Household Budget Survey (KIHBS), 2015/2016 / Kenya National Bureau of Statistics	http://statistics.knbs.or.ke (Basic report on wellbeing in Kenya)
Kyrgyzstan	4.2	per capita consumption	Official Statistics on Living Standards, 2018 / National Statistical Committee of the Kyrgyz Republic	http://www.stat.kg
Lebanon	15.6	per capita consumption	Household Budget Survey, 2011 / Central Administration of Statistics (CAS) and the World Bank	https://www.worldbank.org/ (Measuring poverty in Lebanon using 2011 HBS Technical report)
Mexico	6.9	per capita income	National Survey of Household Income and Expenditure (ENIGH), 2018 / National Council for the Evaluation of Social Development Policy (CONEVAL)	https://www.coneval.org.mx/ (Medicion de la Pobreza)
Mozambique	1.7	per capita consumption	Inquérito aos Orçamentos Familiares, 2014/2015 / The World Bank, National Institute of Statistics of Mozambique	https://www.worldbank.org/ (Strong but not Broadly Shared Growth. Mozambique Poverty Assessment)
Namibia	2.7	per capita consumption	Namibia Household Expenditure Survey, 2015/2016 / Namibia Statistics Agency	https://nsa.org.na/ (Namibia Household Income and Expenditure Survey (NHIES) 2015/2016 Report)
Nigeria	3.2	per capita consumption	Nigeria General Household Survey (NGHS), 2018/2019 / National Bureau of Statistics	http://www.nigerianstat.gov.ng (authors' calculation using ECMVA 2014)
Pakistan	2.9	per capita consumption	Household Income and Expenditure Survey, 2015/2016 / The World Bank	https://worldbank.org (Redaelli (2019), Pakistan at 100 : From Poverty to Equity)
Paraguay	6.8	per capita income	Encuesta Permanente de Hogares, 2017 / Dirección General de Estadistica, Encuestas y Censos	https://www.dgeec.gov.py (Principales Resultados de Pobreza y Distribucion del Ingreso)
Peru	5.8	per capita consumption	National Household Survey, 2018 / National Institute of Statistics and Informatics (INEI)	https://www.inei.gob.pe (Evolucion de la Pobreza Monetaria 2007-2018, Informe Tecnico)
Philippines	3.1	per capita income	Family Income and Expenditure Survey, 2018 / Philippine Statistics Authority	https://psa.gov.ph (Poverty Incidence and Magnitude of Poor Families with Measures of Precision, by Region and Province)
Rwanda	1.3	per capita consumption	The Fifth Integrated Household Living Conditions Survey (EICV5), 2016/2017 / National Institute of Statistics of Rwanda	https://www.statistics.gov.rw (Rwanda Poverty Profile Report)
Senegal	2.9	per capita consumption	Deuxième Enquête de Suivi de la Pauvreté au Sénégal, 2011 / Agence Nationale de la Statistique et de la Démographie	https://www.ansd.sn (Rapport Definitif)
South Africa	3.6	per capita consumption	South Africa Living Conditions Survey, 2014/2015 / Statistics South Africa	https://www.gov.za (authors' calculation using South Africa LCS 2014/2015)
Togo	3.8	per capita consumption	Questionnaire Unifié des Indicateurs de Base du Bien-être (QUIBB), 2015 / Institut National de la Statistique et des Etudes Economiques et Demographiques	https://inseed.tg/ (Cartographie de la pauvrete)
Turkey	12.1	per capita income	Income and Living Conditions Survey, 2018 / TurkStat	http://www.turkstat.gov.tr/ (Poverty Statistics)
Uganda	1.2	per capita consumption	Uganda National Household Survey, 2016/2017 / Uganda Bureau of Statistics	https://www.ubos.org/ (Poverty Maps of Uganda, Technical Report)
Uruguay	8.8	per capita income	Encuesta Continua de Hogares, 2019 / Observatorio Territorio Uruguay (OPP)	https://otu.opp.gub.uy/ (Poverty Statistics by Department)
Zimbabwe	4.2	per capita consumption	Poverty Income Consumption and Expenditure Survey (PICES), 2017 / Zimbabwe National Statistics Agency	http://www.zimstat.co.zw/ (Zimbabwe Poverty Report 2017)

* in 2011 PPP dollars per capita per day

Table A2. Description of Poverty Data

B. Main Approach: Detailed Description and Additional Results

Detailed Description. We provide here a detailed explanation of our main empirical approach when decomposing the timeline into three distinct periods. Let us consider the simplified diagram below, representing mobility patterns over time for poor (P) and nonpoor (NP) regions. We distinguish three periods as follows: 0 corresponds to the pre-COVID-19 situation, 1 the period during which SHO are enforced but without IS, 2 the days with both SHO and IS in place. This simplified sequence corresponds to the reality of most of the countries in our sample and, if not all, is sufficiently representative for our argument.



If we focus on periods 0 and 1, we may extract the differential effect of SHO between lower-poverty and higher-poverty regions by a difference-in-difference (DD) strategy where the average difference P1-NP1 is corrected from the pre-lockdown difference P0-NP0. Yet the analysis diverges from a classic DD. The correction for the first difference P0-NP0 is not very important. Indeed, the pre-pandemic trends in mobility – or region FE identified on the period 0 – are not very informative of how each type of region may respond when the virus and the economic crisis strike. This is all the more an issue if the analysis compares regions of the world. Implicitly in this case, it faces the problem of accounting for differences between *countries* in several factors (i.e. differences regarding pandemic trends, economic trends, state capacities to enforce measures, the evolution of threat perceptions and citizen compliance, etc.). This issue applies to the alternative approach presented in appendix C below and to the previous version of this paper (Aminjonov et al., 2021). It is also related to criticisms of COVID-19 analyses of DD analyses based on country variation (cf. Goodman-Bacon and Marcus, 2020). Thus, our main analysis focuses exclusively on the within-country heterogeneity between higher- and lower-poverty regions, with the regional poverty dummy $Poverty_i$ being defined relatively to the country-specific median and all time-varying confounders being absorbed by country-day effects θ_{ct}. Hence, the approach is not so much a standard DD analysis, rather a suggestive measure of the mobility gap between higher- and lower-poverty regions when SHO are in place. In a model applied to sub-periods 0 and 1, mobility in a subnational region i of country c on day t is written as:

$$Mobility_{ict} = \alpha + \beta Poverty_i \times SHO_{ct} + \theta_{ct} + \mu_i + \varepsilon_{it} \quad (A1)$$

with SHO_{ct} a dummy variable indicating whether any type of SHO was enforced in this country on that day. Coefficient β captures the heterogeneity of interest, namely the poverty gap in mobility when SHO are introduced, which corresponds to a mix of the spontaneous self-isolation during period 1 and the reinforcing effects of SHO measures. We control in μ_i for the pre-crisis regional poverty status (variable $Poverty_i$) and additional regional characteristics such as population density and trust.[18]

Let us now consider period 2. On the diagram above, we represent mobility trends in the counterfactual situation without IS ($NP_2{}'$ and $P_2{}'$) and in the actual situation with IS (NP_2 and P_2), conjecturing that IS programs have succeeded in further reducing mobility. The effect of IS on the poverty gap is simply the actual poverty gap $\Delta_2 = P_2 - NP_2$ minus the counterfactual poverty gap $\Delta_2{}' = (P_2' - NP_2')$. A DD approach would consist in using $\Delta_1 = P_1 - NP_1$ in place of $\Delta_2{}'$ for each country while netting out all time-varying country-specific confounders using country-time effects. The reasoning is now a bit different compared to periods 0 and 1: in contrast to Δ_0, which we have described as providing little information, Δ_1 already gives an indication of regional responses (and their differences) to the health and economic shocks. Then, a model focusing on periods 1 (SHO alone) and 2 (SHO with IS) can be written:

$$Mobility_{ict} = \alpha + \gamma Poverty_i \times IS_{ct} + \theta_{ct} + \mu_i + \varepsilon_{it} \qquad (A2)$$

with θ_{ct} absorbing time-varying confounders. The latter term also absorbs the overall effect of IS in each country, which is not a problem since we focus here on the heterogeneous effect γ, i.e. the poverty gap when IS programs are in place.

As suggested in the main text, we can estimate both (A1) and (A2) simultaneously by considering all three periods and the model:

$$Mobility_{ict} = \alpha + \beta Poverty_i \times SHO_{ct} + \gamma Poverty_i \times SHO_{ct} \times IS_{ct} + \theta_{ct} + \mu_i + \varepsilon_{it} \qquad (A3)$$

Country-day effects θ_{ct} absorb all country-specific time variation including the policy mix at each point in time (SH, IS or both) and the underlying country trends in mobility due to other factors (country-specific evolutions of the pandemic, of the economic situation, of compliance, of health coverage, etc.). Coefficient β captures the poverty gap when only SHO are enforced; γ captures the correction effect of IS, i.e. a catching-up in mobility reduction by the poor thanks to IS.[19] Note that by construction, we ignore here and in the empirical application the

[18] These variables are also interacted with SHO or IS dummies in our robustness checks in order to test alternative mechanisms beyond our work-related interpretation of the poverty gap.

[19] Admittedly, from the description above, it is tempting to interpret the *relative* effect -γ/β as the percentage reduction in the poverty gap due to IS. This is necessarily an approximation: for instance, the relative effect may be overstated if the counterfactual Δ_2' was effectively larger than Δ_1. Ideally, one would use observation just around the time when IS is introduced (i.e. around the second vertical line on the diagram) to limit the influence of time changes. Yet, we have checked that in most countries, there were no sharp changes in mobility just after the introduction of IS, but rather a gradual change as illustrated by the dashed lines on the diagram above. Using observations around the cutoff would not capture the full effect of IS that may take time to materialize.

few days during which SHO are lifted while IS is still operational. This is relatively innocuous and concerns a marginal share of our observations (5.1% of days on average per country).

Additional Results: Varying SHO Stringency. Regarding the different stringency levels of SHO, we use OxCGRT (2020)'s information on the degree of strictness of social distancing policies. The original variable differentiates four levels of SHO by increasing degree of strictness: (a) no stay-at-home orders, (b) recommended staying at home, (c) required staying at home with exceptions for "essential" trips, and (d) required staying at home with minimum exceptions. If we use a discrete variable reflecting these variations instead of the binary variable for SHO, the main finding is a smaller poverty gap in mobility when stringency is high, simply because people had to comply more due to police controls. This unreported result, available from the authors, is not very central and, hence, is not discussed in the main text.

Additional Results: Varying IS Intensity. Regarding the intensity of IS programs, OxCGRT (2020) reports only broad information on IS levels, with high/low IS corresponding to transfers that cover more/less than half of the earnings losses due to the pandemic. Only few countries are concerned by high IS programs: three of them have implemented high IS directly (Gabon, Honduras, Cambodia, Turkey) while two countries have first activated low-level IS then eventually raised the transfers to the high level (Chile, Uruguay). We could reproduce our estimations using ternary groups (no IS, low IS, high IS) rather than the binary IS variable. Yet, we would infer an intensive-margin effect mainly from the comparison of low-IS countries with high-IS countries. In a more robust way, we can compare country-day cells around the switch from low to high IS within a country. For Chile and Uruguay, the two countries in which this switch is observed, the expected pattern is indeed found: more mobility reduction is achieved when IS transfers become larger. Precisely, the poverty gap during period 1 (days with SHO but no IS) is 6.4**, the reduction of this gap due to low IS is -4.8 (insignificant) and the reduction due to high IS is -7.1*** (the sample size is only 18% of the initial sample). This result is mentioned in the main text and, even if concerning only two countries, supports our main interpretation that IS helps reduce the mobility poverty gap.

Additional Results: Heterogeneity across IS Policy Types. In the earlier version of this paper (Aminjonov et al., 2021), we explored the heterogeneity across different types of IS policies using Gentilini et al. (2020). It is important to know which types of social assistance program have been most effective in helping people to stay home. Yet we now refrain to pursue this investigation because the data – at least the version available at the time we wrote this paper – do not allow to conclude in a robust way. Indeed, with the data at hand, it is only possible to characterize whether a country has implemented horizontal expansions (increase in the coverage of existing programs or implementation of new schemes) or both horizontal and vertical expansions (the latter corresponding to an increase in value or duration of transfers for existing beneficiaries) *over the whole period*. It is not possible to know which specific policy option was used at a given point in time and hence use within-country time variation.

C. Alternative Approach: Global Poverty

We can choose an alternative definition of poverty, whereby higher- and lower-poverty regions are defined according to the *global* median of regional poverty rate. In this case, the model exploits time-varying changes in policy across regions of the world so that country-day fixed effects cannot be used anymore. This different perspective may be interesting for a sensitivity analysis of how the poverty gap in mobility changes with the introduction of IS. Yet, compared to the model described above and used in the main text, a two-way fixed effect estimator comparing regions globally is more vulnerable to the critiques made about DD approaches in the context of COVID-19 analyses (e.g. Goodman-Bacon and Marcus, 2020). In essence, the problem is when researchers attempt to compare the evolution of countries A (where a policy got implemented) and B (where it was not). Even if common trends in mobility are respected between A and B, they are not very informative about the way A may evolve – and evolve differently from B - in the absence of the policy. The same problem occurs here when using regions of the world.

The model is written as follows. Mobility in region i on day t is regressed as:

$$\begin{aligned} Mobility_{it} &= \alpha' + \delta SHO_{ct} + \beta' Poverty_i \times SHO_{ct} \\ &+ \rho SHO_{ct} \times IS_{ct} + \gamma' Poverty_i \times SHO_{ct} \times IS_{ct} + \theta_t + \mu'_i + e_{it} \end{aligned} \quad (A4)$$

with SHO_{ct} and IS_{ct} the binary indicators of days with SHO and IS respectively. $Poverty_i$ is a binary measure of poverty indicating whether poverty rate in region i is above (higher poverty) the *global* median of regional poverty rates. The advantage of this formulation is that we can also measure the effect of SHO and IS in lower-poverty regions, i.e. δ and ρ respectively. Coefficients β' and γ' capture the additional effects of SHO and IS for higher-poverty region (the poverty gap in mobility). Day dummies θ_t capture flexible time trends that are common to all (for instance, global information on the pandemic at any point in time, specific announcements by the WHO regarding the virus or the use of masks, etc.). Since we compare regions globally, it might seem important to account for region FE, μ'_i. We do so but recall that these effects, identified on pre-pandemic days, are not very informative. In principle, one would need to control more explicitly for information on country/region heterogeneity (e.g. difference in local healthcare capacities, SHO enforcement capacities, etc.).

Estimation results corresponding to equation (A4) are reported in **Table A3.** Column (i) shows basic estimates for all regions in the sample, with observations reweighted by the inverse of the number of regions per country (not to overweight regions with a large number of regions). For the estimates in column (ii), we additionally control for the lagged cumulative COVID-19 cases. This variable provides additional time variation in the behavioral responses to the local pandemic situation.[20] As noted above, the fact that we ignore country-day effects

[20] Indeed, the pure fear response to the spread of the virus is already captured to a large extent by the SHO variable, since lockdowns were enacted at the time of exponential chances in contamination. Consequently, it is not surprising that this additional variable does not affect results much. Note that we use one-day lagged *nationwide* COVID-19 cumulative cases drawn from the European Center for Disease and Control (ECDC, cf. https://www.ecdc.europa.eu). Information on the count of cases at the regional level is not systematically available.

makes that here, we can identify absolute SHO/IS effects (the 1st and 3rd rows of the table) and not just the relative effect for the poorest.

Results are as follows. Mobility decreases by around 11.9 points in lower-poverty regions when SHO are introduced. Yet, the poverty gap in mobility is 8.2, implying that mobility decreases by only 3.7 points in the higher-poverty regions, i.e. a 69% smaller reduction compared to other regions. IS contributes to a reduced mobility by 3.7 points in regions with lower poverty incidence, and by an additional 3.6 points in higher-poverty regions, decreasing the poverty gap in mobility by that much. The remaining gap is small, i.e. around 4.6 points (8.2-3.6) or 29% of the total mobility reduction in lower-poverty regions. In these regions, the total mobility drop (11.9+3.7=15.6) in periods combining SHO and IS is essentially due to lockdowns (they account for ¾ of the effect versus ¼ for IS transfers) while in higher-poverty regions, the total mobility reduction (15.6-4.6=11) is rather on account of IS policies (2/3 of the effect). The way higher-poverty regions catch up in terms of mobility reduction thanks to IS would be even more pronounced in these regions – corresponding mainly to poor countries in Africa – if they had more resources to support living standards.[21]

Dep. Var.: Mobility to Workplace	All countries		Africa	Latin America	Middle East & Asia
	(i)	(ii)	(iii)	(iv)	(v)
Stay-at-Home	-11.935***	-11.894***	-2.339	-7.245***	-16.595***
	(0.872)	(0.874)	(1.874)	(1.296)	(1.017)
Stay-at-Home X Poverty	8.214***	8.206***	7.755***	1.310	5.487***
	(1.235)	(1.233)	(2.274)	(1.848)	(1.507)
Income Support	-3.702***	-3.660***	-5.167***	-3.055**	-3.098***
	(0.702)	(0.703)	(1.596)	(1.418)	(1.003)
Income Support X Poverty	-3.636***	-3.628***	2.618	-2.924*	-3.877***
	(0.904)	(0.902)	(1.850)	(1.596)	(1.201)
R-squared	0.742	0.742	0.713	0.776	0.764
Observations	142,601	142,601	36,462	61,452	44,687
Day FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Region reweighting	Yes	Yes	Yes	Yes	Yes
Lagged COVID-19 information	No	Yes	Yes	Yes	Yes

Source: authors' estimation using Google reports for workplace mobility, regional poverty rates (from national statistics or authors' estimations as described in Table A1) and the information on COVID-19 policy response from OxCGRT for the period February 15-September 3, 2020. Stay-at-Home is a dummy indicating period in which national stay-at-home orders (recommendations or requirements) are imposed. Income support is a dummy indicating period in which any type of income support was provided in response to COVID-19 pandemic. Poverty is defined as lower (higher) if region's poverty rate is below (above) median poverty rate based on the sample of all 729 subnational regions across 43 countries (columns (i) and (ii)) or the sample of regions within a continent/group of countries being considered (columns (iii)-(vii)). Robustness checks include the lagged cumulative number of COVID-19 cases as control (the data from the European Centre for Disease Prevention and Control). Region reweighting: observations are weighted by 1 over the # of regions in the corresponding country. Standard errors clustered at region level in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table A3. Mobility Effect of Stay-at-Home Orders, Income Support and Poverty

Additional estimations on the subset of countries where this information is available lead to very similar findings. Results are also unchanged when we use the number of fatalities rather than the number of cases.

[21] The social protection coverage in Africa is overall weaker: new transfers reach less than 10% of the population in a majority of countries, and according to the data by Gentilini et al. (2020), the overall expenses on emergency social protection are small ($8.3 billion, i.e. 0.4% of the African GDP, against 1.2% GDP in Latin America in 2020).

The rest of **Table A3** shows results for different geographical areas. The reduction in mobility is generally low in Africa, which is probably due to higher poverty than on other continents and the nature of labor markets. Mobility reduction is larger in Latin America and much larger in Asian countries. This monotonic pattern is consistent with differences in poverty rates across these three continents (44.6%, 33.4% and 15.1% respectively), which supports our poverty interpretation also at the international level. Differences in mobility might additionally reveal, to some extent, differences in both the prevalence of COVID-19 and the stringency of local measures.

Regarding the poverty gap in mobility, it is measured here across regions within each continent (higher-poverty regions are defined according to the median of each continent). It is larger in Africa, partly because the gap in poverty itself is very large there (the average poverty rate in lower-poverty regions of the continent is 23.6% vs. 65.6% in higher-poverty regions). This result is consistent with what we find in the main text but the reason is different: in the baseline model, it is due to the fact that marked regional differences in poverty are also observed *within* African countries.

The change in perspective, i.e. from a model exploiting regional variability within countries to one that exploits both within and between-country variability, is more visible when we consider the impact of IS. Baseline results, using *within-country* dynamics, indicated that especially in African countries, transfers helped poorer regions more than less poor regions. Here, we see in **Table A3** that when comparing regions globally, IS programs are very effective in Latin America and Asia, i.e. they help the poorest regions reduce their mobility relatively more, but not in Africa. Again, this result reflects the fact that, to a large extent, we are now implicitly comparing the relative performance of countries. In Africa, the lower-poverty regions are mainly those from Botswana, Namibia, Cape Verde, Gabon, Egypt and South Africa, where IS programs are most effective than in poorer regions of the continent. In Latin America, the lower-poverty regions are those for instance from Brazil and Mexico, countries where populist presidents have denied the seriousness of the pandemic (Blofield, Hoffmann, & Llanos, 2020).

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