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Poverty and COVID-19 in Africa and Latin America

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ABSTRACT

Since March 2020, governments have recommended or enacted lockdown policies to curb the spread of COVID-19. Yet, poorer segments of the population cannot afford to stay at home and must continue to work. In this paper, we test whether work-related mobility is effectively influenced by the local intensity of poverty. To do so, we exploit poverty data and Google mobility data for 242 regions of nine Latin American and African countries. We find that the drop in work-related mobility during the first lockdown period was indeed significantly lower in high-poverty regions compared to other regions. We also illustrate how higher poverty has induced a faster spread of the virus. The policy implication is that social protection measures in the form of food or cash transfers must be complementary to physical distancing measures. Further research must evaluate how such transfers, when implemented, have attenuated the difference between poor and non-poor regions in terms of exposure to the virus.

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1. Introduction

With the global outbreak of the COVID-19 pandemic, governments announced shelter-in-place and physical distancing policies. In the absence of a vaccine, such measures remained crucial to stop the spread of the virus. Yet, stringent containment policies may hurt poor regions of the world. Poor households have limited savings and food stocks, can rarely work remotely, and often rely on daily hands-on labor income. Thus, remaining stranded during lockdown periods put them at a high risk of extreme poverty.[1] They may face hunger (Ravallion, 2020), turn to negative coping mechanisms (such as lower-quality diets) or simply decide to continue to work and, hence, become more exposed to potential infection (World Health Organization, 2020). This is all the more the case as many countries do not have social safety nets or find it difficulty

to reach the poor, who overwhelmingly work in informal employment (Alon, Kim, Lagakos, & VanVuren, 2020).[2]

> "At the same time while dealing with a COVID-19 pandemic, we are also on the brink of a hunger pandemic." (David Beasley, UN World Food Programme Executive Director).[3]

In the present paper, we address this issue by mobilizing regional data from several Latin American and African countries. We measure how daily mobility to work has changed after the implementation of lockdown policies depending on the subnational level of poverty. We conjecture that in the poorest regions, work mobility is higher than in other regions due to a lower degree of compliance to lockdown measures or, more generally, less opportunity for voluntary containment. Note that several independent studies sug-

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[1] Several studies discuss poverty implications of the COVID-19 pandemic. For instance, Gutiérrez-Romero and Ahamed (2021) estimate that the number of people living below $5.50 a day could go up by 231 million, with nearly half of them pushed in extreme poverty.

[2] The issue has been raised also in the context of rich countries, like the US, where income inequality is still significant and safety nets are modest. As a result, counties with lower levels of per capita income record lower level of compliance with stay-at-home orders (Wright, Sonin, Driscoll, & Wilson, 2020). A survey by Bodas and Peleg (2020) in Israel shows that securing livelihoods during the lockdown, especially for those who are likely to face substantial income losses, is an important factor that can boost compliance. In general, advanced economies are more prepared to complement unprecedented lockdowns with social assistance and ensure compliance (Alon et al., 2020).

[3] See World Food Programme (2020) for a full statement to UN Security Council.

gest a similar approach by looking at regional differences in wealth or economic activity. Yet, they all focus on specific countries. For instance, Durizzo, Asiedu, Van der Merwe, Van Niekerk, and Günther (2021) use a recent survey conducted in two poor neighborhoods of Ghana and South Africa. They find that the main factor that impedes cooperation with containment policies is poverty and the lack of infrastructure. Carlitz and Makhura (2021), focusing on South Africa, also note that implementing lockdown in poor areas represents more challenges, especially in relation to compliance with physical distancing rules. Bennett (2021) find that lockdown policies were more effective in reducing COVID-19 cases in high-income municipalities of Chile, partially due to the disparities in mobility response to containment measures.

Our empirical approach is as follows. We combine regional information from Google COVID-19 mobility reports and comprehensive poverty statistics at the same sub-national level, i.e. across 242 regions of 9 countries from Latin America and Africa. We cover a period of 71 days starting from February 16, 2020, including the pre-lockdown period and the first period of containment. This way, we can conduct a difference-in-difference estimation around the time of lockdown announcements. The main variable of interest, i.e. work mobility, drops very substantially around that date. We test if work mobility during lockdown is higher in poorer regions, relatively to prior mobility levels. The daily panel of regions allows us to account for regional fixed effects in the estimations and, hence, to capture fundamental differences across regions (e.g. differences in healthcare capacities, local culture, perception about COVID-19, or the timing of the epidemic such as the date of the first contaminations).[4]

We find that the decrease in work mobility after lockdown announcements is significantly smaller in subnational regions with higher poverty rates. Consistently with our interpretation, the effect of poverty is stronger for mobility that is related to work compared to other activities. This implies that poor people are less likely to comply with self-isolation requirements – or are less able to stay at home spontaneously – and rather continue their labor activities by commuting to their workplaces. We further illustrate that a smaller mobility reduction in high-poverty areas during lockdown translates into a faster spread of COVID-19. Our calculations indicate that a standard deviation above the mean regional poverty is associated with 11% more cases after a month and a half. Overall, this study demonstrates that poor people in Africa especially, and Latin America to some extent, cannot afford to follow confinement as much as others because of the hardest choice they face during the pandemic between taking the risk to get infected or falling in extreme poverty.

2. Data

This study mobilizes several types of data: the Google mobility index, sub-national poverty rates, and statistics on daily cases of COVID-19.

2.1. Mobility

We use daily human mobility data from Google COVID-19 mobility reports, which aggregate anonymized data sets from users' mobile device Location History. These reports record percent changes in the number of visits or length of stay at various locations compared to a reference period of January 3 – February 6, 2020. There are six location categories: (i) retail and recreation, (ii) grocery and pharmacy, (iii) parks, (iv) transit stations, (v) workplaces, and (vi) residential areas. We focus on a subset of the Google mobility data covering subnational regions of nine countries in Africa (Egypt, Kenya, Nigeria, South Africa) and Latin America (Argentina, Brazil, Colombia, Mexico, Peru) for a period from February 16 to April 26, 2020.[5]

Fig. 1 illustrates work mobility using national mean levels (similar trends are obtained with other mobility categories).[6] The horizontal axis represents the February 16-April 26 periods, with March 1 taken as day 0. The calls for self-isolation were made around March 16–20 in Latin American countries, slightly later in African countries. We see that work mobility declines in all countries after mid-March, with a sharp drop in most cases (or a more progressive trends in some countries such as Kenya, Nigeria and Mexico). Note that different rates of change in mobility reflect several factors, including the timing and stringency of national lockdowns, and spontaneous behavior, possibly in relation to local factors such as poverty. The cross-country variance in mobility is relatively small before the lockdown period and increases enormously afterwards due to the variety of country responses.

2.2. Poverty

We combine mobility data with poverty statistics at the level of subnational regions. Poverty is measured as headcount ratios (the share of people living below national or international poverty lines in a region). For graphical analysis, we use discretized versions of regional headcount ratio: binary and terciles. A binary poverty measure takes the value one if the poverty headcount ratio is above the national average of regional poverty rates, and zero otherwise. Tercile measures are a set of dummy variables defining levels of regional poverty as low (below 25th percentile of regional poverty rate within a country), medium (between 25th-75th percentiles), and high (above 75th percentile). For estimations, we use both regional poverty rate directly, as a continuous measure of poverty, and its discretized versions.

We rely on official poverty statistics and, when missing (i.e. for Nigeria and South Africa), on our calculations using recent available household surveys. Datasets and methodological choices are explained in much detail in Table A.1 in the appendix.[7] Note that our results are not very dependent on these methodological choices, especially the choice of the poverty line: our difference-in-difference (DID) approach essentially compares regional time variation in poverty (controlling for regional fixed effects), rather than differences in poverty levels across regions. We will nonetheless check our results using alternative poverty measures, namely extreme poverty rather than moderate poverty (see Table A.1). Our final sample (with non-missing values on key variables) includes 242 subnational regions observed over 71 days from February 16, 2020.

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[4] Note that mobile phone tracking has already been used for gauging the mobility impact of travel restrictions, for instance during the unprecedented measures put in place to eliminate Ebola in 2015 (Peak et al., 2018, for Sierra Leone). Google reports have been used to check how mobility and poverty correlate at country level analysis (UNDP, 2020). Yet, many dimensions vary across countries that may confound the effect of poverty. This justifies the approach suggested in the paper using both region and time variations in a difference-in-difference analysis.

[5] At the time we set up this analysis, Google mobility data at the subnational level was available for a few low- and middle-income countries only. The latest data versions provided by Google cover a larger number of countries and regions. For further detail, see Google LLC (2020).

[6] We transform the mobility data, for a matter of convenience, from the percent changes into an index on a 0–100 scale, where the reference level of mobility is equal to 100. For example, work-related mobility with the value of 85 for the governorate of Cairo on March 20 corresponds to a 15 percent decrease in mobility for this type of activity and this place compared to the reference period.

[7] All poverty measures are based on per capita income or consumption. Poverty thresholds are either the standard World Bank international poverty lines (for different income groups of countries) or national definitions based on the value of a basic bundle of goods (or basic food basket, for extreme poverty).
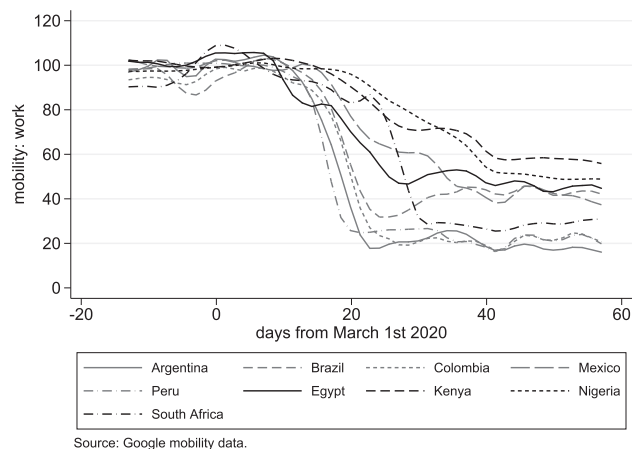
Fig. 1. National Trends in Mobility to Work.

2.3. COVID-19 cases

To explore health externalities in the context of the COVID-19 pandemic, we assess how the effect of poverty on mobility reflects on the spread of the virus. We use the daily updates of the European Centre for Disease Prevention and Control (ECDC) on the number of COVID-19 cases. Our estimations will also include robustness checks where we control for the (one-day lagged) number of cumulative COVID-19 cases.

3. Empirical approaches and results

3.1. Graphical evidence

We start with a visual examination of regional mobility patterns by poverty levels, focusing on the whole period from February 16 to April 26, 2020.[8] In Fig. 2, we illustrate regional mobility trends for work-related locations, that is, the type of mobility for which we expect the largest impact of poverty. Each graph represents the daily average mobility across all regions. Here we use the terciles of poverty, splitting regions into the groups of low, medium, and high poverty as defined above. The vertical dashed line represents the average lockdown date in the countries included in our sample.

In the first graph of Fig. 2, we see that mobility fluctuates around 100 in late February and early March, that is, around the same level as in the reference period. All poverty groups show similar mobility patterns during this early stage, both in trends and levels. Following lockdown measures, there is a sharp drop in mobility, which is more pronounced for regions with lower poverty rates and less marked for very poor regions. This pattern constitutes our main result. The second and third graphs focus on each continent separately. Comparing both graphs, we see that the overall mobility reduction is smaller in Africa than in Latin America,

suggesting the role of poverty differences at a broader scale. Also, the gap between high- and low-poverty regions is larger within the African sample. This possibly denotes a stronger dispersion in living standards and/or in behavioral responses across African regions.[9] We obtain very similar patterns when considering extreme poverty measures in analogous graphs (see Fig. A.2 in the appendix).

In Fig. 3, we compare the patterns of workplace mobility with other mobility categories. We distinguish here only two poverty groups (high/low) but conclusions are identical with three. For all mobility types, we observe similar trends over the complete period. Yet the difference between high- and low-poverty regions is much larger for work-related mobility in comparison to other mobility types. This result suggests that less spontaneous containment – or less compliance to lockdown policies – among the poor is mostly driven by life-and-death motives which force them to continue income-related activities during a lockdown. Finally, notice that mobility reductions are highest for non-essential activities (recreation and transits) and smallest for going to the grocery/pharmacy, while work mobility is somewhat intermediary.

3.2. Difference-in-difference panel estimations

We proceed with econometric estimation to formally test whether mobility response to lockdown varies across regions with different poverty levels, as observed in the graphical evidence above.

Difference-in-difference approach. We adopt a DID approach to estimate the effect of poverty on mobility trends during the COVID-19 pandemic. Estimations are conducted on our panel of regions × days over the period from March 1 to April 26. We regress the mobility of type j (e.g. work-related mobility) in region i on day t as follows:
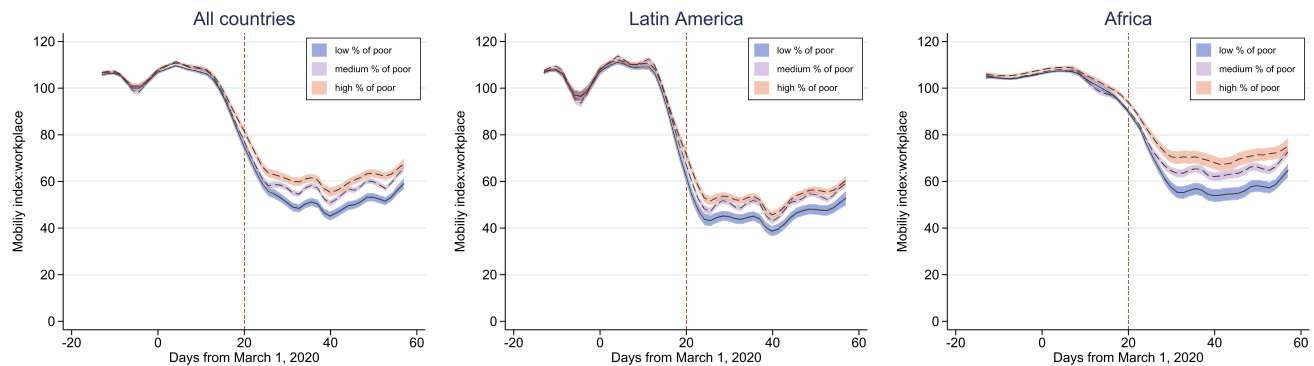
$$Mobility_{it}^{j} = \alpha + \gamma Post_t \times Poverty_i + \mu_i + \theta_t + \varepsilon_{it}. \tag{1}$$

Recall that initial lockdown announcements in our sample of countries took place in a narrow interval around March 20. Thus, we can use this average lockdown date as the cutoff to determine the 'treatment' period, formally noted as $Post_t = 1(t > \text{March20})$.[10] For the interaction term in (1), $Poverty_i$ is the headcount ratio (continuous version) or a discrete version: either a dummy indicating if regional poverty is above the national average or terciles of poverty (dummies indicating a moderate and high level of regional poverty, relatively to low-poverty regions).[11] Coefficient γ is the DID estimator, representing the mobility effect of being in higher poverty regions during lockdown. Day dummies θ_t capture common time trends (for instance, the information available to everyone on the pandemic situation at any point in time). Region fixed effects μ_i account for country characteristics (e.g., overall contagion level, policy stringency, health systems) and regional characteristics (e.g.,

[8] Because of the level of trade with China, Egypt and South Africa were the countries at highest importation risk in Africa, as estimated using destination air travel flows (Gilbert et al., 2020). Africa confirmed its first case in Egypt on Feb 14, 2020.

[9] With rare exceptions, a similar pattern with monotonic ranking is found when looking at each country separately (see Fig. A.1 in the appendix). Only exceptions concern two Latin American countries, Brazil and Mexico. The explanation may pertain to specific situations in countries where populist presidents from the right (Brazil) or left (Mexico) deny the seriousness of the pandemic (Blofield, Hoffmann, & Llanos, 2020). While subnational and other authorities seek to fill the leadership vacuum, policy implementation is harmed and self-containment is low for both the rich and the poor. Note that work mobility levels in these countries are the highest among the Latin American countries represented in Fig. 1 and Fig. A.1

[10] The results that follow are similar when starting the period of observation on Feb. 16 rather than March 1, or when using alternative definitions of $Post_t$. For the latter, we have experimented with earlier dates (corresponding to international announcement of the pandemic situation), continent-specific dates (Africa or Latin America average dates of lockdown calls) or country-specific dates (using announcement dates of strict lockdown policies or of recommendations at national or sub-national levels, as reported at: www.bbc.com/news/world-52103747). Some of these sensitivity checks are presented hereafter.

[11] Note that $Poverty_i$ itself does not appear in Eq. (1) because it is treated as a constant characteristic of a region for the few weeks of interest, hence absorbed by region fixed effects μ_i. Similarly, $Post_t$ is absorbed by day dummies θ_t.

[12] Note that the validity of the DID approach requires that for the groups of different 'treatment' intensity, outcomes show parallel trends in absence of treatment. We have verified this condition in the graphical analysis above, namely that groups of regions have common trends in mobility (and even show very similar mobility levels). Formal tests confirm it. We estimate Eq. (1) on the period from February 16 to March 10 (beginning of the drop in Mobility) for different values of $Post_t$ in this interval and find no effect of regional poverty on mobility.

Source: author's calculations based on Google mobility data (mobility for workplace) and poverty data from national statistics offices and authors' estimations using household surveys.
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 in region living below national/international poverty lines.
% of poor is defined as low if region's poverty rate is below 25th percentile of regional poverty rates within country, medium if between 25th and 75th percentile, and high if above 75th percentile.

Fig. 2. Mobility to Workplaces by Levels of Regional Poverty.

Source: author's calculations based on Google mobility data and poverty data from national statistics offices and authors' estimations using household surveys.
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 in the region living below national/international poverty lines.
% of poor is defined as low (high) if region's poverty rate is below (above) country's average poverty rate.

Fig. 3. Mobility to Workplaces versus Other Locations by Poverty Groups.

local healthcare capacities, long-term labor market and economic characteristics determining local standards of living) that can be treated as constant over the period.

Main results. Table 1 reports DID estimates for work-related mobility.[12] We start with binary poverty. Consistent with the graphical analysis, the estimates of γ confirm that the decrease in work-related mobility due to lockdown is significantly smaller in high-poverty regions. We interpret this as a lower level of compliance with national stay-at-home orders. The effect is around 4 mobility points (on the 0–100 scale), equivalent to 9.3% of the average drop in mobility during lockdown (43 mobility points). Table 2.

We consider several specifications that all yield very similar estimates in that order of magnitude. First, column (A) controls for day dummies and country fixed effects. Column (B) corresponds to our main specification laid out in Eq. (1). As explained, it includes region fixed effects that capture local (time-invariant) unobserved heterogeneity, including persistent determinants of poverty. Column (C) controls additionally for the cumulative number of COVID-19 cases reported at the national level on $t - 1$. It rep-

resents the objective risk of contagion and the urgency to comply with containment measures, which may alter mobility behavior.[13] Another potential issue is that pooling countries with varying numbers of regions may result in a larger weight attached to a country with numerous regions. To avoid this, column (D) checks the sensitivity of the estimates from (B) to reweighting each observation by the inverse of the number of regions in the corresponding country. The coefficient slightly falls in magnitude but remains positive and significant. Columns (E) and (F) report the results of regressions analogous to column (B), but separately for African and Latin American countries. As observed in Fig. 2, there is a stronger mobility effect of poverty in Africa compared to Latin America. Lastly, column (G) excludes Brazil which is found to be an outlier among Latin American countries in the graphical analysis (see Fig. A.1 in the appendix). The coefficient for Latin America slightly increases when excluding Brazil.

The next rows of Table 1 convey similar conclusions, using alternative poverty outcomes. The tercile approach shows a monotonic pattern: mobility reduction due to confinement is around 7.8 points smaller in high-poverty regions and 4 points smaller in

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[12] Note that the validity of the DID approach requires that for the groups of different 'treatment' intensity, outcomes show parallel trends in absence of treatment. We have verified this condition in the graphical analysis above, namely that groups of regions have common trends in mobility (and even show very similar mobility levels). Formal tests confirm it. We estimate Eq. (1) on the period from February 16 to March 10 (beginning of the drop in Mobility) for different values of $Post_t$ in this interval and find no effect of regional poverty on mobility.

[13] Note that alternative estimations using the number of new cases or the cumulative number of deaths lead to similar results (significant estimates of 4.038 and 4.012 respectively). Since the perception of the situation may vary across regions, we also interact the number of cases with region dummies μ_i, which yields estimates that are slightly larger but in the same order of magnitude (4.421 using cumulative cases and 5.063 using new cases).

Table 1
Effect of Poverty on Mobility.

	All countries				Africa	Latin America	Latin America (excl.Brazil)
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Binary Poverty							
Post x Poverty	4.035***	4.018***	4.033***	3.331***	6.643***	3.509***	4.187***
	(0.512)	(0.500)	(0.500)	(0.528)	(0.584)	(0.570)	(0.655)
R-squared	0.766	0.806	0.806	0.812	0.773	0.885	0.884
Terciles of Poverty							
Post x Moderate Poverty	4.079***	4.070***	4.077***	4.395***	6.149***	3.423***	3.964***
	(0.615)	(0.606)	(0.606)	(0.640)	(0.708)	(0.723)	(0.822)
Post x High Poverty	7.819***	7.798***	7.798***	7.447***	10.816***	5.972***	7.353***
	(0.709)	(0.700)	(0.699)	(0.745)	(0.813)	(0.808)	(0.927)
R-squared	0.769	0.807	0.807	0.813	0.775	0.885	0.885
Regional Poverty Rate (Continuous)							
Post x Poverty	0.329***	0.329***	0.345***	0.302***	0.194***	0.071***	0.236***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.020)	(0.023)
R-squared	0.787	0.823	0.823	0.824	0.781	0.884	0.886
Observations	13,664	13,664	13,664	13,664	6,140	7,524	5,985
Day Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No	No	No
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged cumulated COVID-19 cases	No	No	Yes	No	No	No	No
Region reweighting	No	No	No	Yes	No	No	No
Mean Mobility (0–100)	74.9	74.9	74.9	73.3	82.8	68.5	65.8
Mean Poverty (%)	38.3	38.3	38.3	38.3	49.6	29.1	32.6
% change in work mobility for:							
+1 % increase in poverty (elast)	0.17	0.17	0.18	0.16	0.12	0.03	0.12
+1 std. dev. in poverty	10.39	10.39	10.90	9.75	6.37	1.54	5.97
% change in upcoming C-19 cases growth rate for:							
+1 % increase in poverty (elast)	0.08	0.08	0.08	0.07	0.05	0.01	0.06
+1 std. dev. in poverty	4.91	4.91	5.15	4.61	3.01	0.73	2.82

Note: Authors' estimation using Google reports for workplace mobility and regional poverty rates (from national statistics or authors' estimations as described in Table A.1) for the period March 1-April 26, 2020. Post is a dummy indicating the period starting March 20, 2020 (average lockdown date). Continuous poverty is the percent of people in the region living below the poverty line. Binary poverty measure corresponds to a dummy indicating if the region's poverty rate is above country average regional poverty rate. Moderate (high) poverty dummies indicate if regional poverty rate is between 25th-75th percentile (above 75th percentile) of regional poverty rates within country. Robustness checks include cumulated number of COVID-19 cases as control (taken from the European Centre for Disease Prevention and Control) and region reweighting (observations are weighted by 1 over the # of regions in the corresponding country). Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 2
Effect of Poverty on Mobility, by Mobility types.

	Work	Retail & Recreation	Grocery & Pharmacy	Transit Stations
	(1)	(2)	(3)	(4)
Post x Poverty (bin.)	4.018***	0.821	1.490***	2.086***
	(0.500)	(0.673)	(0.559)	(0.655)
P-value: coef. equal to that of Work		0.00	0.00	0.00
Observations	13,664	12,506	12,173	11,359
R-squared	0.806	0.838	0.846	0.722

Note: Authors' estimation using Google reports for workplace mobility and regional poverty rates (from national statistics or authors' estimations as described in Table A1) for the period March 1-April 26, 2020. Post is a dummy indicating the period starting March 20, 2020 (average lockdown date). All estimations include region fixed effects and day fixed effects. Poverty (bin.) is a dummy indicating if region's poverty rate is above national average regional poverty rate (the percent of people in the region living below national/international poverty lines). Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

moderate-poverty regions compared to low-poverty regions. The effects are fairly large, especially for high-poverty regions, corresponding to 18.1% and 9.3% of the average drop in mobility, respectively. Finally, we explore the complete variation in regional poverty by using headcount ratios directly. The estimates show that an additional percentage point in the regional poverty rate is associated with 0.33 points higher mobility during lockdown. In other words, a one standard deviation difference in regional poverty rate (23.6 percentage points) would yield a mobility differen-

tial of around 7.8 (equivalent to 18.1% of the average drop in mobility).

[15] This is also reflected in the fact that global production and price of key food commodities remained at or close to pre-pandemic levels.
[16] For instance Aguirre and Hannan (2020) and Campos-Vazquez and Esquivel (2020) for Mexico, Niembro and Calá (2020) for Argentina, Bennett (2021) for Chile, Durizzo et al. (2021) and Carlitz and Makhura (2021) for South Africa, Kansiime et al. (2021) and Janssens et al., 2021 for Kenya. See also González-Bustamante (2021) for South America.
[17] For the countries in our sample, we find a growth rate in smartphone ownership between 2015 and 2018 of 47% on average (own calculations based on PEW reports). Smartphone ownership rates in 2015 were 48% in Argentina, 41% in Brazil, 35% in Mexico, 26% in Kenya, 28% in Nigeria and 37% in Argentina (Pew Research Center, 2016).

[14] It essentially boils down to poverty rates calculated using the World Bank PPP $1.9 poverty line rather than higher national or international thresholds as described in Table A.1.

At the bottom of Table 1, we provide elasticity estimates for the effect of poverty on mobility and on the spread of COVID-19 (the latter is discussed in the next section). We calculate mobility elasticities as a one percent or a one standard deviation departure from the mean regional poverty (38.3 percentage points), but similar results are obtained using a log–log specification of Eq. (1). For instance, with the baseline model (B), a 1% (resp. one standard deviation) increase in regional poverty leads to a 0.17% (resp. 10.4%) increase in work mobility.

Sensitivity checks. We provide sensitivity analyses in Table A.2 in the appendix. We first report DID estimates based on the same approach as above but changing the time cutoff to March 11 - the date when WHO declared COVID-19 as a global pandemic. With this definition of $Post_t$, we obtain the results compared to the benchmark estimates. The second set of results is based on extreme poverty rates as an alternative definition of poverty.[14] Given that DID estimates are identified by comparing relative changes in regional poverty over time, we expect methodological aspects surrounding poverty calculations not to alter our conclusions too much. The results for the average effect over all countries (columns A-D) are very close to the baseline. We find a larger effect of extreme poverty in Africa and a more modest effect for Latin American countries.

Alternative mobility indices. We compare the effect of poverty across different types of mobility to check whether the non-compliance of poor people with confinement is mostly due to the urgency to meet their basic life needs through daily earnings. We estimate our baseline model (DID with region and time fixed effects) using binary poverty and, as an outcome, work mobility or three other types of mobility: retail and recreation, grocery and pharmacy, and transit stations. Results are reported in Table 2. The estimates show that the effect of poverty is positive on other types of mobility, but it is the largest for work-related mobility. This result is consistent with Fig. 3. It also seems intuitive that the largest effect among other activities pertains to time spent in transports (transit stations), as it is partly related to work behavior. The formal tests of equality of the coefficients confirm that the poverty effect is significantly larger for mobility to workplaces, compared to the other three types of mobility (the equality of coefficients is rejected with a p-value close to zero in all three cases).

Interpretation. Our results suggest that poorer people exhibit lower compliance with self-isolation recommendations, as they have no choice other than continuing income-generating activities to survive during the pandemic. As argued in the introduction, people in poor areas tend to be informal salary or self-employed workers (e.g. daily laborers and street traders). Hence, they have limited remote work options and are difficult to reach for aid agencies. Nonetheless, we would not see a difference in mobility between high and low poverty regions if there was no longer any possibility of working anywhere. Several elements lend additional credence to our interpretation. We argue that *to some extent*, there was still a demand for goods and services in poorer communities during lockdowns as well as operational workplaces for the poor to work and make a living. In urban regions, many low-wage workers are found in services deemed essential, such as grocery stores and delivery services, but also food processing factories and distribution. The latter, and the agricultural sector in rural regions, have been broadly operational to avoid disruptions in food supply (World Bank, 2020).[15] In rural areas, a fraction of the poor rural workers could continue to work on farms – to the extent that they had access to inputs and to markets – or to live from their own food production. A large part of the non-agricultural economy of the poor regions is fragmented in small production units for goods (e.g. handcraft) and services (e.g. trade on local markets). Some of their activity may have continued, despite initial announcements regarding the closure of outdoor markets and the ban on street vendors. Local public debate about the trade-off between health risks and hunger risks have indeed led to many exceptions, including in countries that have imposed strict lockdowns such as South Africa (Devereux, Béné, & Hoddinott, 2020). That said, our results show that poor regions have also decreased work mobility a lot. This is partly due to the fact that many poor households could actually not continue to work (especially when they were predominantly employed in industries that were hardly hit, such as tourism or the manufactures impacted by the drop in global demand). International and national aid programs may have also helped some of them during containment. There is possibly a broad heterogeneity of situations across regions, which is analyzed at country level in several studies.[16]

Limitations and discussion. We finally discuss the potential limitations of using Google COVID-19 mobility reports. As noted before, it is an aggregate and anonymized data from Google Location History (GLH) in users' mobile devices. Admittedly, this mobility data is possibly biased towards more educated and wealthier individuals who are more likely to own a smartphone and use mobile Internet (Ballivian, Azevedo, & Durbin, 2015). Note, however, that Android devices are increasingly popular in low- and middle-income settings as an affordable way to access the Internet (Ruktanonchai, Ruktanonchai, Floyd, & Tatem, 2018). According to a report by Pew Research Center (2019), the average smartphone ownership rate in 2018 was around 45% in emerging economies (76% in advanced economies). Among the countries included in our study, this rate was 68% in Argentina, 60% in Brazil, 52% in Mexico, 41% in Kenya, 39% in Nigeria, and 60% in South Africa. In Columbia and Peru, smartphone ownership rate was 53% and 36% respectively, according to our calculations based on the 2018 Latinobarometer. Although still lower than in rich countries, digital and mobile connectivity has rapidly expanded in middle and low income nations over the last years.[17] Moreover, the latest statistics for mobile penetration rates in these countries show that cellular subscriptions have reached an average of 115 per 100 people (see Table A.3 in the appendix). Overall, these statistics reassure us that Google mobility data does not represent a marginal share of the populations covered in our analysis. Furthermore, it is likely that we underestimate mobility differences across regions. Indeed, GLH information may capture the mobility of the least poor within poor regions, i.e. those who could reduce their mobility the most. Thus, the effect of poverty on mobility that we estimate in the presence of this potential bias can still serve as an interesting lower bound of the true effect. According to our results, it is large enough to underline that poverty is an important determinant of compliance with containment policies in Africa and Latin America.

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[14] It essentially boils down to poverty rates calculated using the World Bank PPP $1.9 poverty line rather than higher national or international thresholds as described in Table A.1.

[15] This is also reflected in the fact that global production and price of key food commodities remained at or close to pre-pandemic levels.

[16] For instance Aguirre and Hannan (2020) and Campos-Vazquez and Esquivel (2020) for Mexico, Niembro and Calá (2020) for Argentina, Bennett (2021) for Chile, Durizzo et al. (2021) and Carlitz and Makhura (2021) for South Africa, Kansiime et al. (2021) and Janssens et al., 2021 for Kenya. See also González-Bustamante (2021) for South America.

[17] For the countries in our sample, we find a growth rate in smartphone ownership between 2015 and 2018 of 47% on average (own calculations based on PEW reports). Smartphone ownership rates in 2015 were 48% in Argentina, 41% in Brazil, 35% in Mexico, 26% in Kenya, 28% in Nigeria and 37% in Argentina (Pew Research Center, 2016).
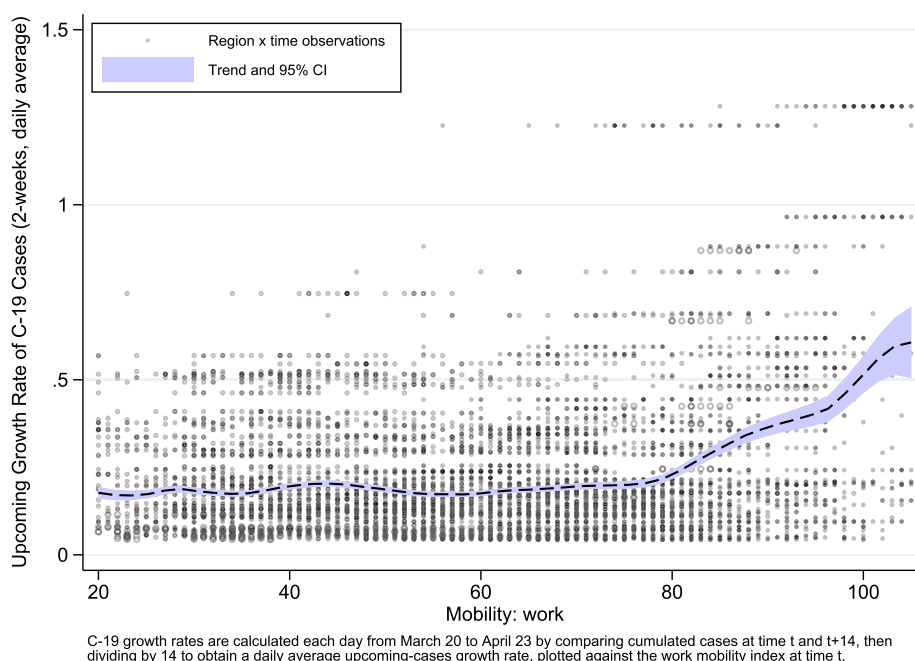
C-19 growth rates are calculated each day from March 20 to April 23 by comparing cumulated cases at time t and t+14, then dividing by 14 to obtain a daily average upcoming-cases growth rate, plotted against the work mobility index at time t.

Fig. 4. Effect of Mobility on Upcoming Growth Rate of COVID-19 Cases.

3.3. Implications for the spread of COVID-19 in Africa and Latin America

Finally, we attempt to provide suggestive evidence on how poverty translates into a higher spread of COVID-19 through increased work mobility. Note that the following calculations are purely indicative. Hereafter, we use daily mobility data and the cumulative number of reported COVID-19 cases for the period from March 20-April 26, 2020.

We first establish how the upcoming growth rate of COVID-19 responds to the instantaneous mobility index, reflecting the time and spatial variation in behavioral responses to lockdown policies. For each day, we compare the current cumulative number of reported COVID-19 cases to that of 2 weeks ahead,[18] and divide the corresponding growth rate by 14 to obtain an average daily growth rate of upcoming COVID-19 cases. This rate implicitly incorporates the exponential nature of the COVID-19 diffusion and the way it is affected by local self-isolation behavior. The link between mobility and this upcoming growth rate is illustrated in Fig. 4. Lower levels of work-related mobility are associated with lower rates of future cases. To calculate an elasticity, we regress upcoming growth rates on mobility, day dummies, region fixed effects and alternative sets of additional controls. Estimates lead to an elasticity of around 0.40-0.47. That is, a 10% increase in mobility leads to a 4%-4.7% increase in the epidemic growth rate (a 0.9-1.1 percentage point increase).[19]

Then, we multiply this elasticity by the mobility-poverty elasticity discussed in the previous section to obtain an elasticity of COVID-19 growth-rate with respect to regional poverty. Results are reported at the bottom of Table 1. We find an elasticity of around 0.07–0.08. That is, a 10% (resp. one standard deviation) higher rate of regional poverty is associated with a 0.8% (resp. 5%) higher growth rate of COVID-19. We can get a notion of how it translates into a number of cases. Note that in the countries of our sample, there were on average 190 cumulative cases by March 20 and around 22,500 cases by May 3 (ECDC figures). With our elasticity, we find that a one standard deviation difference in poverty between two regions corresponds to a difference of 11% on May 3 (around 2,500 cases) and 14% after two months.[20]

4. Conclusion

While physical distancing helps to slow the spread of the COVID-19, it can carry a high cost for poor workers, who have little savings and critically rely on casual labor to cover basic needs for survival. As a result, the poor are more likely to show lower compliance with containment rules by continuing labor activities. Using daily mobility data for nine African and Latin American countries, we consistently show that the decline in work-related mobility during lockdown is significantly smaller in subnational regions with higher poverty rates. We further characterized how the rate of virus diffusion increases with poverty through this channel.

Thus, lockdowns that are not accompanied by adequate social transfer programs are less likely to elicit broad compliance and can have serious consequences for vulnerable households. In poor countries, containment policies must be combined with consumption support. This aid can take the form of transfers in cash, if food

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[18] A two-week lag used for the growth rate calculation is the average known duration between infection and public report. Results are similar when using 1 or 3 weeks.

[19] From the different specifications, we obtain significant estimates ranging between 0.0015 and 0.0018. They are multiplied by the mean mobility index over this period (59.9) and divided by the average daily epidemic growth rate (0.22, i.e. a doubling in the number of cases in less than five days on average) to yield elasticities. Note that our elasticities are a lower bound of what is currently found in the literature. Using a different international data (covering Asian and Western countries), Soucy et al. (2020) find that a 10% decrease in relative mobility in the second week of March was associated with a 11.8% relative decrease in the average daily death growth rate in the fourth week of March, i.e. an elasticity of 1.18.

[20] These results are qualitatively consistent with IMF recent simulations based on epidemiological models (Dizioli & Pinheiro, 2020). They show that wealthier individuals can lower their infection risk because they have the option of working less and limiting time spent outside their homes. Globally, the simulations indicate that rich households have around five times less chances to ever get infected by the virus over a two-year period.
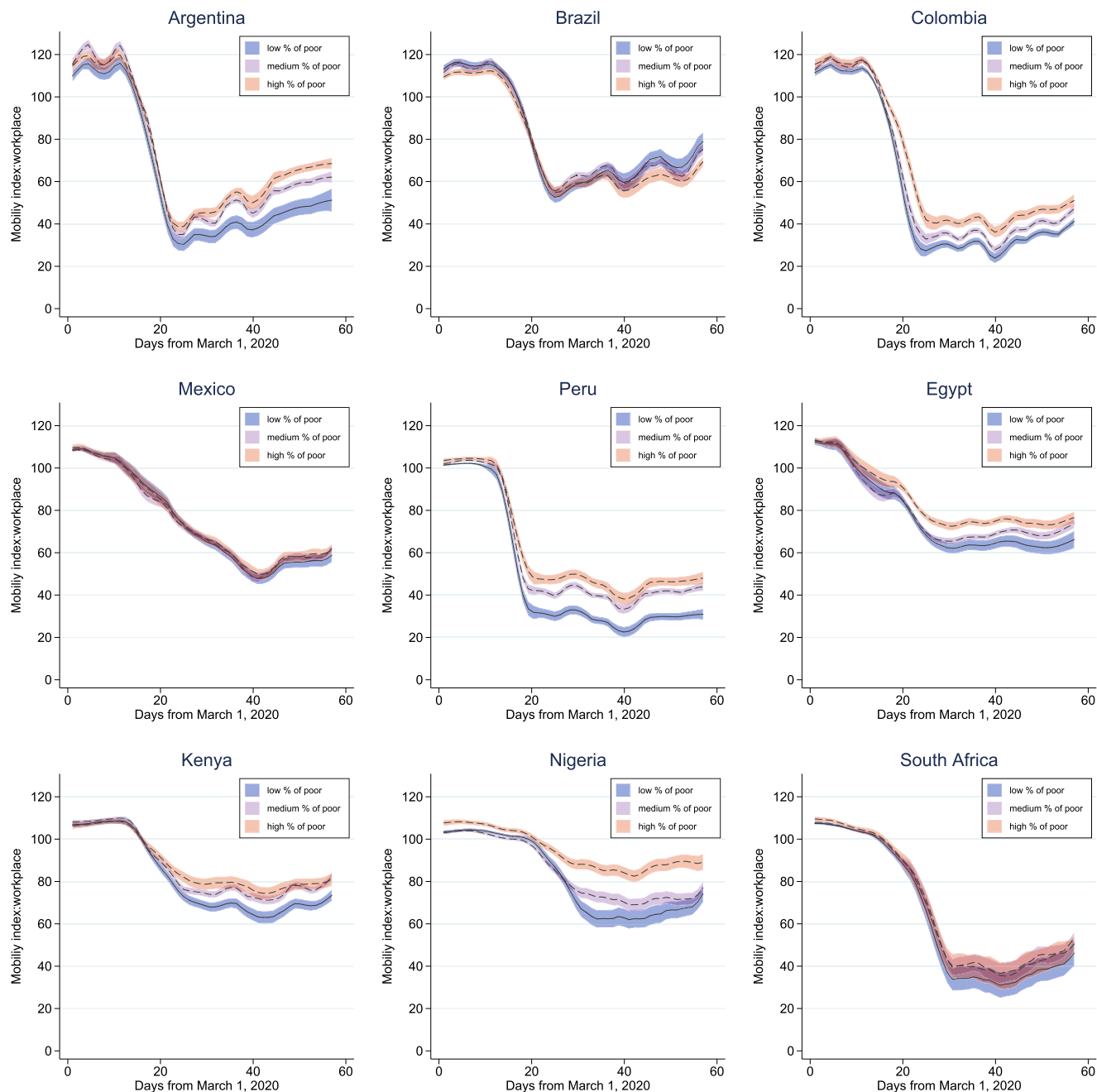
**Fig. A.1.** Work Mobility by Regional Poverty Levels (All Countries).

markets are working, or in-kind benefits otherwise (Ravallion, 2020). Many low-income countries are utilizing both existing and new cash transfer schemes to reach the vulnerable groups during the pandemic (see detailed policy strategies in Gerard, Imbert, & Orkin, 2020).[21] An obvious option is to scale up these schemes through temporary modifications such as removing work or

school-attendance requirements.[22] Finally, if no effective pre-existing system is in place, other strategies can be considered, such as geographical targeting based on poverty maps and epidemiological/containment maps (McBride & Nichols, 2018).[23]

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[21] For instance, the Government of Kenya introduced additional payments for the beneficiaries of the *Inau Jamii* program to cushion vulnerable groups (i.e. the elderly, orphans and persons with disabilities) from the negative effects of the pandemic. In addition, around 3 million new beneficiaries were added to the National Safety Net Program (NSNP) and the Kenya Social and Economic Inclusion Project (KSEIP). In Colombia, on top of the existing safety net schemes, new cash transfer programs such as *Ingreso Solidario* and *Bogotá Solidaria En Casa* were implemented to target informal workers and vulnerable groups and to prevent them from leaving homes for daily subsistence income (Gentilini, Almenfi, Orton, & Dale, 2020).

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[22] For example, the Colombian government announced that children benefiting from the school feeding program *Programa de Alimentacion Escolar* would continue receiving meals at home during the COVID-19-induced school closures. A consideration for pursuing targeted cash transfers to deal with COVID-19 is whether they can fit in with the delivery system of existing schemes and whether the latter has proven effective (Beegle, Coudouel, & Monsalve, 2018; Gentilini, 2020).
[23] Combining high-resolution satellite images with machine learning algorithms and census data to identify vulnerable neighborhoods has proven to work well in the case of Columbia. Namely, beneficiaries of the new cash transfer programs were identified based on the data from the social program and tax collection systems, census data, cell phone operators and other district-level databases (Gentilini et al., 2020).
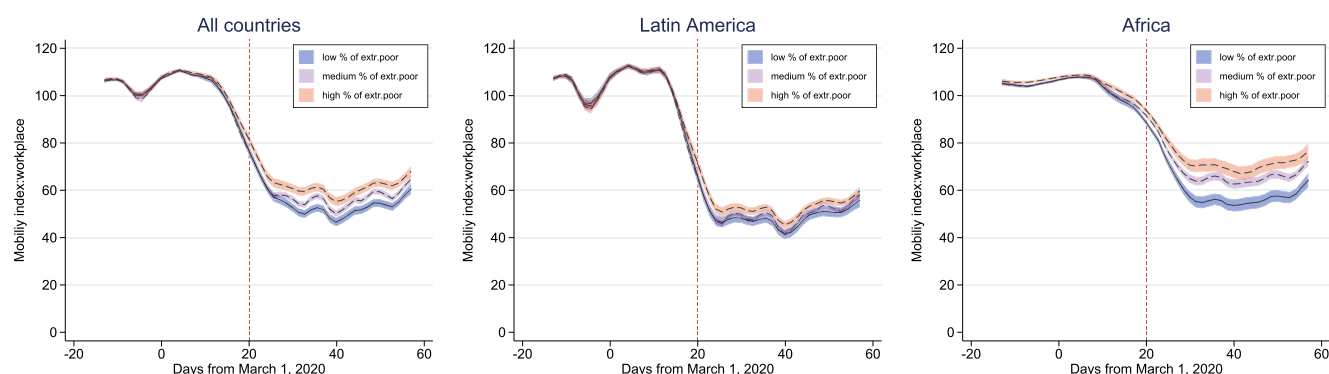
Source: author's calculations based on Google mobility data (mobility for workplace) and poverty data from national statistics offices and authors' estimations using household surveys.
Local polynomial fit with 95% CI of daily mobility across regions, weighted by (1/# of regions in the corresponding country). Extreme poverty is measured as the share of people in region living below national/international extreme poverty lines. % of extremely poor is defined as low if region's poverty rate is below 25th percentile of regional poverty rates within country, medium if between 25th and 75th percentile, and high if above 75th percentile.

Fig. A.2. Mobility to Workplaces by Levels of Extreme Poverty.

Several research paths are suggested. First, since current policy action is monitored in real-time (Gentilini et al., 2020), future research could investigate whether social transfers, such as those described above, have promoted compliance with self-isolation requirements during the pandemic. Second, as smartphone ownership and mobile internet usage are still relatively low in Latin America and Africa, corrections could be brought to our measures for imputation of daily mobility changes in nationally representative surveys (see the approach in Pokhriyal & Jacques, 2017; Steele et al., 2017 or Blumenstock, Cadamuro, & On, 2015).

Finally, similar methodologies could be applied to other parts of the world, in particular in South Asia where the human cost of lockdown may be huge given that a quarter of the population makes their living from casual occupations (Ray & Subramanian, 2020). In this context, a major event is the "reverse migration" of informal workers from urban workplaces to their rural homes, after they lost their job due to nationwide lockdowns. This has been described as the largest mass migration since the 1947 parti-

tion of India. It is a source of concern because of the extreme poverty of millions of migrants, stranded in different locations en route to their native villages, but also because of critical health externalities (i.e. international migration has substantially intensified the spread of the virus, see Lee, Mahmud, Morduch, Ravindran, & Shonchoy, 2020).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Figs. A.1,A.2 and Tables A.1,A.2,A.3.

Table A.1
List of Sources of Regional Poverty Data.

Country	Data source/Organization, Year	Living std measure	Moderate/extreme poverty lines in PPP $ per capita per day*	Weblink
Argentina	Permanent Household Survey (EPH)/National Institute of Statistics and Census of Argentina (INDEC), 2019	Per capita household income	National moderate/extreme poverty line: 9.8/2.49 [WB: 5.5/1.9]	https://www.indec.gob.ar (Condiciones de vida Vol. 4, No. 4)*
Brazil	Continuous National Household Survey (PNAD Continua)/Brazilian Institute of Geography and Statistics (IBGE), 2018	Per capita household income	WB moderate/extreme poverty line for upper middle income countries: 5.5/1.9	https://www.ibge.gov.br/estatisticas/ (Sintese-de-Indicadores-Sociais-2019)
Colombia	Integrated Household Survey (GEIH)/National Administrative Department of Statistics (DANE), 2018	Per capita household income	National moderate/extreme poverty line: 5.45/2.49 [WB: 5.5/1.9]	https://www.dane.gov.co/ (condiciones vida, pobreza monetaria 18 departamentos)
Egypt	Household Income, Expenditure and Consumption Survey (HIECS)/Central Agency for Public Mobilization and Statistics (CAPMAS), 2015	Per capita household consumption	National moderate/extreme poverty line: 6.25/4.14 [3.2/1.9]	Regional poverty calculated by El-Laithy and Armanious, 2018 based (HIECS),https://www.capmas.gov.eg
Kenya	Kenya Integrated Household Budget Survey (KIHBS), Kenya National Bureau of Statistics, 2015/16	Per capita household consumption	National moderate (extreme) poverty line: 3.11/1.51	http://statistics.knbs.or.ke/nada/index.php/catalog/88/ (Basic Report on Wellbeing in Kenya)
Mexico	National Survey of Household Income and Expenditure (ENIGH)/National Council for the Evaluation of Social Development Policy (CONEVAL), 2018	Per capita household income	National moderate (extreme) poverty line: 6.96/3.62 [WB: 5.5/1.9]	https://www.coneval.org.mx/Medicion/Paginas/PobrezaInicio.aspx
Nigeria	Nigeria General Household Survey (NGHS)/National bureau of statistics, 2018/19	Per capita household consumption	WB moderate (extreme) poverty line for lower middle income country: 3.2/1.9	Authors' calculation based on NGHS,http://www.nigerianstat.gov.ng/nada/index.php/catalog/62/overview
Peru	National Household Survey/National Institute of Statistics and Informatics (INEI), 2017	Per capita household	National moderate (extreme) poverty line: 5.95/3.16 [5.5/	https://www.inei.gob.pe/estadisticas/indice-tematico/sociales/ (Población con al menos una

Table A.1 (*continued*)

Country	Data source/Organization, Year	Living std measure	Moderate/extreme poverty lines in PPP $ per capita per day*	Weblink
		consumption	1.9]	necesidad básica insatisfecha, según departamento)
South Africa	South Africa Living Conditions Survey (SA-LCS)/ Statistics South Africa, 2014/15	Per capita household consumption	WB international moderate (extreme) poverty line for upper middle income countries: 5.5/1.9	Authors' calculation based on SA-LCS, https://www.gov.za/ss/statssa-living-conditions-survey

Note: Regional poverty is calculated as the headcount ratio, i.e. # of people with per capita household income/consumption, below indicated poverty lines (moderate or extreme). The table summarizes the relevant information about data used, data providers, living standard measure (consumption or income), poverty lines, and weblink to access the data.

* World Bank international poverty line for moderate poverty depends on the country income group (low, lower-middle or upper-middle income countries indicated in red, green, blue respectively). When national poverty lines are used, they typically correspond to the minimum amount covering the basic consumption basket (for extreme poverty lines: the basic food basket/nutrition requirement). In this case, we indicate PPP values for a comparison with the WB poverty lines of the country's income group indicated in square bracket. Note that international poverty lines are the standard for cross-country poverty comparisons due to their simplicity (https://blogs.worldbank.org/developmenttalk/richer-array-international-poverty-lines) but are overly sensitive to measurements of PPP exchange rates and domestic consumer price indexes, especially for countries with high inflation and a volatile exchange rate such as Argentina. Notice for Argentina the difference in poverty line between World Bank Latin America international threshold Ferreira et al., 2012 and the national poverty line CEDLAS, 2017. See OECD Economic Surveys: Argentina 2017, at:https://www.oecd-ilibrary.org/sites/eco_surveys-arg-2017-6-en/index.html?itemId=/content/component/eco_surveys-arg-2017-6-en

Table A.2
Effect of Poverty on Mobility: Additional Robustness Checks.

	All countries				Africa	Latin America	Latin America (excl.Brazil)
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
March 11th as Cutoff Date							
Post x Poverty (bin.)	4.327***	4.322***	4.334***	3.883***	6.771***	3.852***	4.346***
	(0.599)	(0.608)	(0.607)	(0.590)	(0.660)	(0.658)	(0.741)
Extreme Poverty							
Post x Extreme Poverty (bin.)	3.540***	3.555***	3.595***	2.298***	6.682***	2.150***	1.774***
	(0.522)	(0.510)	(0.510)	(0.537)	(0.595)	(0.569)	(0.665)
Observations	13,664	13,664	13,664	13,664	6,140	7,524	5,985
Day Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No	No	No
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged cumulated COVID-19 cases	No	No	Yes	No	No	No	No
Region reweighting	No	No	No	Yes	No	No	No

Note: Authors' estimation using Google reports for workplace mobility and regional poverty rates (from national statistics or authors' estimations as described in Table A1) for the period March 1-April 26, 2020. Post is a dummy indicating the period starting March 11, 2020 (WHO declaration of COVID-19 as pandemic) or March 20th, 2020 (average lockdown date) for estimation with extreme poverty. Poverty (bin.)/Extreme poverty (bin.) is a dummy indicating whether a region's poverty/extreme poverty rate is above country's average. Region reweighting: observations are weighted by (1/# of regions in the corresponding country). Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3
Mobile Phone Penetration Rates.

Country	Penetration Rate	Indicator	Source	Reporting period
Argentina	126	# accesses per 100 inhabitants	Ente Nacional de Comunicaciones	4th quarter 2019
Brazil	90.63	density of mobile telephony per 100 inhabitant	National Telecommunications Agency	March 2020
Colombia	129.26	# accesses per 100 inhabitants	Ministry of Information Technologies and Communications	3rd quarter 2019
Egypt	95.59	# accesses per 100 inhabitants	Ministry of Communications and Information Technology	February 2020
Kenya	114.8	# SIM per 100 inhabitants	Communications Authority of Kenya	December 2019
Mexico	95.7	# service lines per 100 inhabitants	Federal Telecommunications Institute	3rd quarter 2019
Nigeria	98.9	# active telephone connections per 100 inhabitants	Nigerian Communications Commission	February 2020
Peru	127.6	# mobile phone lines per 100 inhabitants	National Institute of Statistics and Informatics	September 2018
South Africa	159.93	# cellular phone subscriptions per 100 inhabitants	ITU World Telecommunication/ICT Indicators database	2018

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2021.105422.

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