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Poverty and COVID-19 in Developing Countries

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Abstract

In March 2020, shelter-in-place and social-distancing policies have been enforced or recom-mended all over the world to fight the COVID-19 pandemic. However, strict containment is hardly achievable in low-income countries, as large parts of population are forced to continue income-generating activities to escape extreme poverty or hunger. To assess the trade-off between poverty and a higher risk of catching COVID-19, we use regional mobility to work and poverty rates across 241 regions of 9 countries from Latin America and Africa. With a difference-in-difference approach around the time of lockdown announcements, we mea-sure the differential time variation in work mobility between high and low-poverty regions. We find that the degree of work mobility reduction is significantly driven by the intensity of poverty. Consistently, human movements vary significantly more between poverty levels when it come to work rather than less vital activities. We also estimate how higher poverty rates translate into a faster spread of COVID-19 cases through the channel of work mobility.

Keywords: COVID-19, poverty, lockdown, compliance, work mobility.

JEL: E71, H12, I12, I18, O15

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Poverty and COVID-19 in Developing Countries

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Abstract

In March 2020, shelter-in-place and social-distancing policies have been enforced or recommended all over the world to fight the COVID-19 pandemic. However, strict containment is hardly achievable in low-income countries, as large parts of population are forced to continue income-generating activities to escape extreme poverty or hunger. To assess the trade-off between poverty and a higher risk of catching COVID-19, we use regional mobility to work and poverty rates across 241 regions of 9 countries from Latin America and Africa. With a difference-in-difference approach around the time of lockdown announcements, we measure the differential time variation in work mobility between high and low-poverty regions. We find that the degree of work mobility reduction is significantly driven by the intensity of poverty. Consistently, human movements vary significantly more between poverty levels when it come to work rather than less vital activities. We also estimate how higher poverty rates translate into a faster spread of COVID-19 cases through the channel of work mobility.

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"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).[1]

1 Introduction

With the global outbreak of the COVID-19 pandemic, shelter-in-place and social-distancing policies have been put in place around the world. In the absence of vaccine, such measures remain crucial to stop the spread of the virus. However, unlike in richer parts of the world, the effectiveness and socio-economic consequences of stringent confinement policies are largely being questioned in the context of low-income countries (Ravallion, 2020, Mobarak and Barnett-Howell, 2020, Piper, 2020). One of the central concerns, among other burning aspects such as fragile healthcare systems, is that a large part of the population of poor countries works in uncovered informal sectors and is reliant on daily hands-on labor income, which is hardly attainable under strict self-isolation requirements (Robalino, 2020). Unless proper safety nets are ensured, poor people in developing countries cannot afford to stay at home and to follow confinement policies simply due to the urgency to feed themselves and their families.[2] Yet, there are almost no empirical studies investigating the effect of poverty on compliance with public health recommendations across developing countries in the time of a global pandemic.

Against this background, we measure how daily mobility to work has changed after the implementation of lockdown policies in Latin America and Africa depending on the local level of poverty. To do so, we combine Google COVID-19 mobility reports and comprehensive poverty statistics at the sub-national level, i.e. across 241 regions of 9 countries from Latin America and Africa, over a period of 71 days starting from February 16, 2020. To measure the effect of poverty on compliance with confinement policies, we adopt a difference-in-difference approach around the time of lockdown announcements to quantify how the time change in work mobility differs across regional poverty levels. We use the daily panel of regions to account for regional fixed effects, which capture fundamental differences across regions (differences in healthcare capacities, local culture or perception about COVID-19, or the timing of the epidemic such as the date of first contaminations).[3]

Our analysis reveals that the decline in work mobility after lockdown is significantly lower in regions with higher poverty rates, i.e. these poorer regions comply less with shelter-in-place policies. This poverty effect is significantly stronger for work mobility compared to other activ-

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

[2] The issue has been raised also in the context of developed countries, like the US where a significant inequality in income levels still persists and makes that US counties with lower levels of per capita income record lower level of compliance with stay-at-home orders (Wright et al., 2020)

[3] 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 are also currently used to check how mobility and poverty correlate at country level analysis (UNDP, 2020). Yet, many other dimensions vary across countries that may confound the effect of poverty. This justifies the approach suggested in the paper using region x day variation and double difference analysis.

ities. In simple terms, poorer people are less likely to comply with self-isolation requirements and stay at home, but more likely to continue their labor activities by commuting to their workplaces. Our results provide a solid empirical evidence that poor people in developing part of the world cannot afford to follow confinement policies as much as non-poor people, roughly due to the hardest choice they face during the time of pandemic between risking to catch COVID-19 or falling in extreme poverty. Finally, we estimate the effect of reduced mobility on the spread of COVID-19 and, subsequently, on how the effect of poverty on mobility translates into higher regional epidemic growth rates. One standard-deviation above the mean regional poverty is associated with 11% more cases after a month and a half.

2 Data Sources

To analyze the impact of poverty on mobility and, then, on the spread of COVID-19, we mobilize several types of data: the Google mobility index, poverty data from various sources, and information on the local numbers of daily cases of COVID-19.

2.1 Mobility

We use daily human mobility data from Google COVID-19 mobility reports, which aggregate anonymized sets of data 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.[4] There are six location categories: (i) retail and recreation, (ii) grocery and pharmacy, (iii) parks (public gardens, dog parks, beaches, etc.), (iv) transit stations (public transport hubs such as subway, bus, train stations), (v) workplaces, and (vi) residential areas. Human mobility is tracked by Google daily and in a consistent manner across 131 countries for a period of 71 days from February 16 to April 26, 2020. For a subset of countries, the information is provided at sub-national level. We focus on the countries for which regional mobility is available in Africa (Egypt, Kenya, Nigeria, South Africa) and Latin America (Peru, Brazil, Argentina, Mexico, Colombia).

The original data is provided in percent changes with respect to average mobility in the reference period. For a matter of convenience, we transform the percent changes into an index on a 0-100 scale, where the reference mobility intensity takes the value of 100. For example, a work-related mobility 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 location compared to the reference level. Figure 1 illustrates work mobility using country mean levels (similar trends are obtained with other mobility categories). 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 observe a decline in mobility in all countries, with a sharp drop in most cases and more progressive trends in some countries

[4]See: https://www.google.com/covid19/mobility/

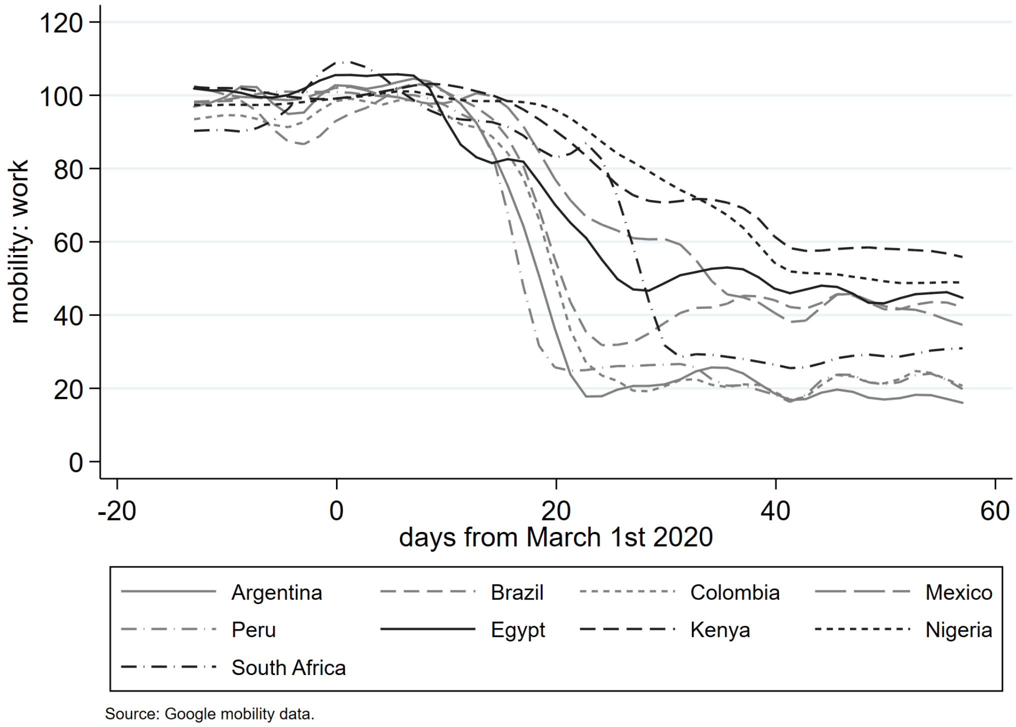


Figure 1: National Trends in Mobility to Work.

(Kenya, Nigeria or Mexico). Note that the cross-country variance in mobility is relatively small before the lockdown period and increases enormously afterwards due to the variety of country responses. The plateau level reached by mobility curves in late March and April varies with national policies, from strict official lockdown to mild mitigations policies (e.g. in Brazil and Mexico). Note that different rates of change in mobility reflect several factors including national lockdown stringencies and spontaneous behavior, possibly in relation with local factors such as poverty.

2.2 Poverty

We combine mobility data with poverty rates at regional level. Poverty is measured as headcount ratios (the share of people living below national or international poverty lines in the region). We rely on relatively recent datasets and use regional poverty measures provided by statistical offices or, when missing (Nigeria and South Africa), based on our own calculations using publicly available household surveys. Datasets and methodological choices are explained in much detail in Table A.1 in the appendix. All poverty measures rely 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).

Our results are not very dependent on these methodological choices (notably the choice of poverty line) because our difference-in-difference approach essentially compares regional time variation in poverty (controlling for region fixed effects) rather that differences in absolute poverty levels across regions, as explained in the empirical approach hereafter. We will nonetheless check our main results when using alternative poverty lines, namely extreme poverty rather than moderate poverty. Our estimations use poverty headcount ratios directly (as a continuous measure of poverty intensity at regional level) or discretized versions. A binary poverty measure is taking value one if regional poverty headcount ratio is above the country 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 country), *medium* (between 25th-75th percentiles) and *high* (above 75th percentile). Binary and tercile measures are convenient for graphical representations and will also be used in the estimations.

2.3 COVID-19 cases

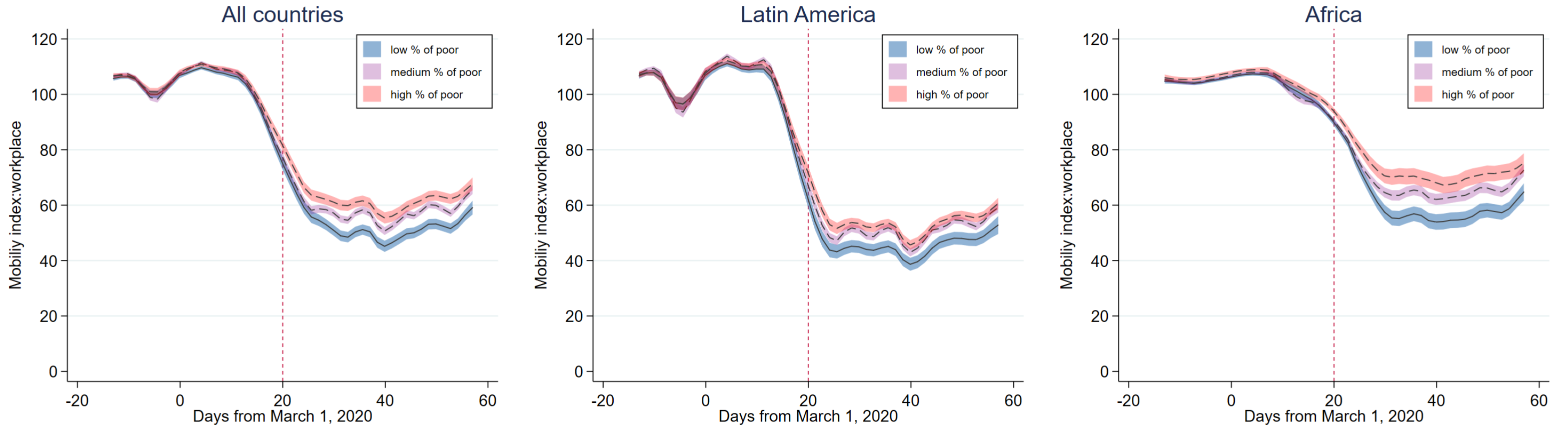
After combining mobility and poverty data, our final sample (with non-missing values on key variables) includes 241 regions in 9 countries from Latin America and Africa over a period of 71 days starting from February 16, 2020. Note that our estimations will include robustness checks whereby the (one-day lagged) number of new COVID-19 cases is included. Also, we ultimately assess how poverty reflects on the growth rate of COVID-19. For both purposes, we use the daily updates of the European Centre for Disease Prevention and Control (ECDC) on the number of COVID-19 cases by country.

3 Empirical Approaches and Results

3.1 Graphical Evidence

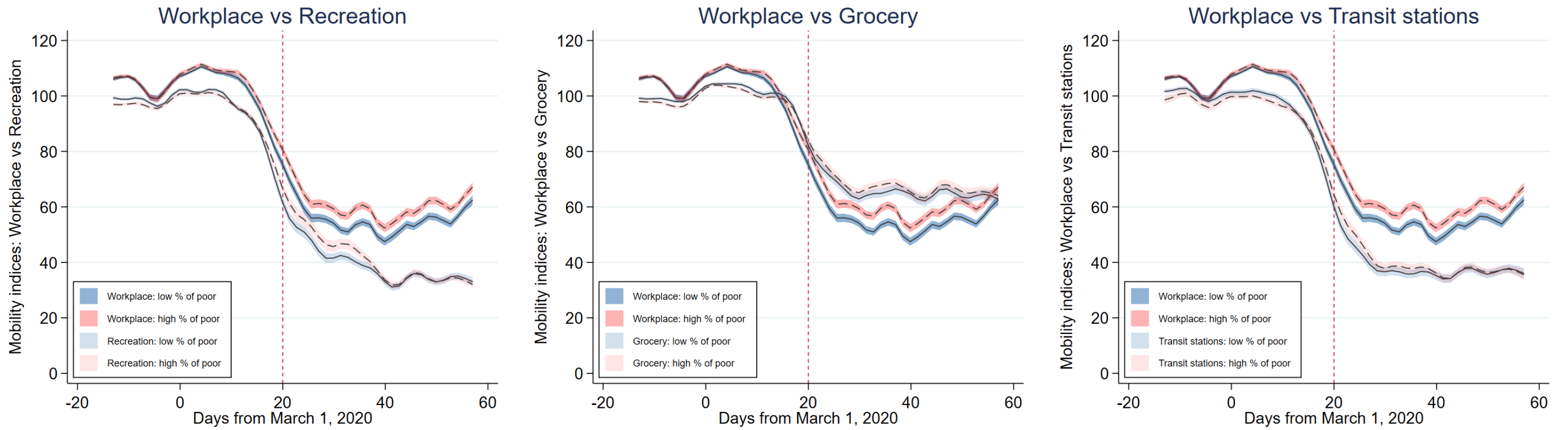
We start with a visual examination of regional mobility patterns by levels of poverty across regions in our sample, focusing on the whole period of available data (February 16 to April 26, 2020).[5] In Figure 2, we illustrate regional mobility trends for work-related locations, i.e. the type of mobility for which we expect the largest impact of poverty. Each graph represents the daily average mobility over all the regions in our sample. We use a local polynomial fit of the daily variation across regions and its 95% confidence interval (CI). The horizontal axis represents dates with March 1 taken as day 0. Here we use terciles of poverty, splitting regions in three groups of low, medium and high poverty levels as defined above. The vertical dashed line represents the average lockdown date in the countries covered in our sample.

[5]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.



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.

Figure 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.

Figure 3: Mobility to Workplaces versus Other Locations by Poverty Groups.

Consider the first graph of the figure. We see that mobility fluctuates around 100 in late February/early March, i.e. around the same level as in the reference period (Jan. 3 - Feb. 6). Most importantly, the different poverty groups show very similar mobility patterns during this early stage, both in trends and levels (differences are often not statistically significant). Following lockdown measures or recommendations, the drop in mobility is significantly more pronounced for low-poverty regions. This pattern constitutes our main result. It is verified using binary poverty (unreported) or in the more detailed representation of Figure 2 with three poverty groups, showing a monotonic relationship between poverty levels and mobility decline.

The second and third graphs focus on each continent separately. Comparing both graphs, we see that the overall mobility reduction is smaller in Africa (between 30% and 40%) compare to Latin America (more than 40%), which suggests the role of poverty differences at a broader scale. Also, differences between high and low poverty regions are more pronounced within the African sample, which possibly denotes more regional dispersion in living standards in Africa and/or more differences in behavioral responses across African regions. In all the graphs, these gaps between poverty groups remain noticeable until the end of the observation period (26th of April).

With rare exceptions, a similar pattern is found when looking at each country separately – see Figure A.1 in the appendix. The monotonic ranking between high, medium and low poverty regions in mobility changes is observed almost everywhere, with statistically significant differences at least between high and low poverty regions. 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 et al., 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.[6]

We also check whether results are sensitive to the definition of poverty at country level. To consider a large change in poverty line, we consider the extreme poverty measures (see Table A.1 for methodological detail). We replicate our approach while grouping regions according to their position in their national distribution of regional 'extreme poverty' rates, namely with low (below 25th percentile), medium (between 25th-75th percentiles) and high (above 75th percentile) groups. Figure A.2 shows very similar patterns compared to the previous results: the drop in mobility levels during lockdown decreases with the regional rate of extreme poverty.

Finally, in Figure 3, we compare the patterns of workplace mobility with other mobility categories. For the sake of clarity, we distinguish 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 groups is much larger for work-related mobility in comparison to other mobility types. This result suggests that less spontaneous con-

[6]In these countries, work mobility levels are actually the highest among the Latin American countries represented in Figure A.1, as also seen in Figure 1.

tainment – or less compliance to lockdown policies – among the poorest is mostly driven by life-and-death motives which force them to continue income-related activities during the lockdown period. A final remark is 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

Given the graphical evidence above, we proceed with econometric estimations aimed to formally test these behavioral differences across regions of different poverty intensity.

Difference-in-difference approach. We adopt a difference-in-difference (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. Precisely, we regress mobility of type j 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 calls for lockdown have taken place in a narrow interval around March 20 so that we use this average lockdown date as the cutoff to determine the 'treatment' period, i.e. formally, we note $Post_t = 1(t > \text{March } 20)$.[7] For the interaction term, $Poverty_i$ is the headcount ratio (continuous version) or a dummy variable indicating if regional poverty is above the national average. We will also use interactions of $Post_t$ with high and medium poverty (low poverty being the reference group) for the tercile version.[8] Coefficient γ is the DiD estimator, representing the effect of higher poverty on mobility during lockdown compared to low poverty regions before 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 dummies μ_i account, among other things, for regional and national disparities in the overall contagion level or in local levels of policy stringencies, for different national health systems or local healthcare capacities, or for persistent regional characteristics (including long-term labor market and economic characteristics determining local standards of living).

Main results. Difference-in-difference estimates for work-related activities are reported in Table 1.[9] We start with binary poverty. Consistent with the graphical analysis, estimates of γ

[7] 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.

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

[9] 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

	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 1: Effect of Poverty on Mobility

confirm that work-related mobility is significantly higher in regions with higher poverty rates during the lockdown period relative to low-poverty regions in the preceding period. It can be interpreted as lower levels of compliance with national stay-at-home orders during the pandemic due to the necessity to work. The magnitude of the effect is around 4 points of mobility (on the 0-100 scale), which represents 4% of the pre-lockdown mobility among low-poverty regions or 6.6% of the overall mobility after March 20. We consider several specifications that all yield very similar estimates in that order of magnitude. First, model (A) controls for day dummies and country fixed effects. Model (B) corresponds to our main specification, i.e. the panel DiD as laid out in equation (1). As explained, it includes region fixed effects that capture local (time-invariant) unobserved heterogeneity, including the persistent determinants of poverty. Model (C) additionally controls for the cumulative number of reported COVID-19 cases at national level on $t-1$. It represents the objective risk of contagion and the urgency to comply with con-

above, namely that groups of regions have common mobility trends (and even show very similar mobility levels). Formal tests confirm it. We estimate equation (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.

tainment measures, which might alter individual mobility behavior.[10] Another potential issue is that pooling countries with varying number of regions may result in larger weight attached to a country with numerous regions. To avoid this, Model (D) checks the sensitivity of model (B)'s estimates to reweighting each observation by the inverse of the number of regions in the corresponding country. The coefficient of interest slightly falls in magnitude but is still positive and significant.

Models (E) and (F) report results of regressions analogous to model (B), but separately for African and Latin American countries. Consistently with Figure 2, and as could be expected, there is a stronger mobility effect of poverty in Africa compared to Latin America. In the last column, model (G) excludes Brazil which was found to be an outlier among Latin American countries in the graphical analysis (see Figure A.1 in the appendix). The coefficient for Latin America excluding Brazil increases slightly.

The next rows of Table 1 convey that conclusions are similar using alternative poverty outcomes. The tercile approach shows a monotonic pattern: mobility reduction due to containment is around 7.8 points smaller in high poverty regions and 4 points smaller in moderate poverty regions compared to low poverty regions. Then, using directly the regional headcount ratio allows using the complete variation in poverty intensity across regions. The estimate means that an additional percentage point in the regional poverty rate is associated with a mobility that is around 0.33 point larger during lockdown. For 1 standard deviation in regional poverty rate (23.6 points), the mobility differential is around 7.8, which is similar to the gap between low and high poverty regions in our tercile approach.

At the bottom of Table 1, we provide elasticity estimates for the effect of poverty on mobility, and ultimately on the growth rate of COVID-19 cases (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 of regional poverty (equal to 38.3 percent) but similar results are obtained using a log-log specification of equation (1). For instance, with the baseline model (B), a 1% (resp. 1 standard deviation) increase in regional poverty leads to a 0.17% (resp. 10.4%) increase in work mobility.

Sensitivity checks. We provide further sensitivity analyses in appendix Table A.2. We first report DiD estimates based on the same approach as above but changing the time cutoff to March 11, 2020, which is the date when WHO declared COVID-19 as a global pandemic. With this definition of $Post_t$, we obtain very similar estimates compared to the baseline. The second set of results is based on alternative definitions of poverty. 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. To experiment

[10] Note that alternative estimations using the number of new cases or the cumulated 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 cumulated cases and 5.063 using new cases).

with a substantial change in poverty line, we consider extreme poverty (it essentially boils down to using the World Bank PPP $1.9 poverty line rather than higher national or international thresholds as described in Table A.1). Regarding the average effect over all countries (models A-D), results are indeed very close to the baseline. Consistently with the graphical analysis of Figure A.2, we see a large 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 non-compliance of poor people with confinement policies are 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 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 most importantly, it is the largest for work-related mobility. This result is consistent with Figure 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 effect of poverty 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). These results confirm that poorer people tend to exhibit lower compliance with self-isolation recommendations as they have no choice other than continuing income-generating activities to survive during pandemic.

	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

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

Limitations and discussion. We discuss potential limitations regarding the use of Google COVID-19 reports to measure human mobility at regional level. Admittedly, mobility data is possibly biased towards more educated and wealthier parts of the population who are more likely to own a smartphone and use the Internet (Ballivian et al., 2015). Yet, Google Location History (GLH) data is available from an increasingly large proportion of the world, as the Android user base has increased dramatically since 2012, reaching over 3 billion active devices in 2020. Moreover, though being still lower than in advanced economies, the rates of smartphone ownership and internet usage in emerging economies have rapidly increased in the recent years (International Telecommunication Union, 2019). In particular, for the countries included in our sample, the latest reported statistics for national mobile penetration rates – subscriptions to cellular services per 100 people – show that access to mobile services is considerably high, with an average of 115 mobile subscriptions per 100 inhabitants (see Table A.3 in the appendix). This reassures us that Google mobility data may still represent large parts of population in the countries covered in our analysis. Furthermore, GLH data is argued to be a promising source of mobility data for a better understanding of daily human movement in low- and middle-income settings where Android devices are increasingly popular as an affordable way to access the Internet (Ruktanonchai et al., 2018). In our analysis, we try to compare mobility across regions with different levels of poverty. Thus, in regions with a low poverty rate, GLH information is likely to capture most of the regional population while in regions with high poverty rates, there is a bias towards the less poor segment of the local population. In this scenario, the difference between a higher level of mobility (lower compliance) among the poor and a lower mobility (higher compliance) of the non-poor during lockdown is likely to be underestimated in our approach. Yet, the effect of poverty on mobility that we estimate in the presence of such potential bias can still serve as a lower bound, which is enough to underline that poverty is one of the important determinants of compliance with containment policies in developing countries.

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 in Latin America and Africa. 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 time and spatial variation in lockdown policies and behavior. For each day, we compare the current cumulated number of reported COVID-19 cases to that of 2 weeks ahead, 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 Figure 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 and region fixed effects. In a set of alternative specifications, we find significant estimates ranging between 0.0015 and 0.0018. Given a mean mobility index of 59.9 over this period, and an average daily epidemic growth rate of 0.22 (a doubling in the number of cases in less than 5 days on average), these estimates yield 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

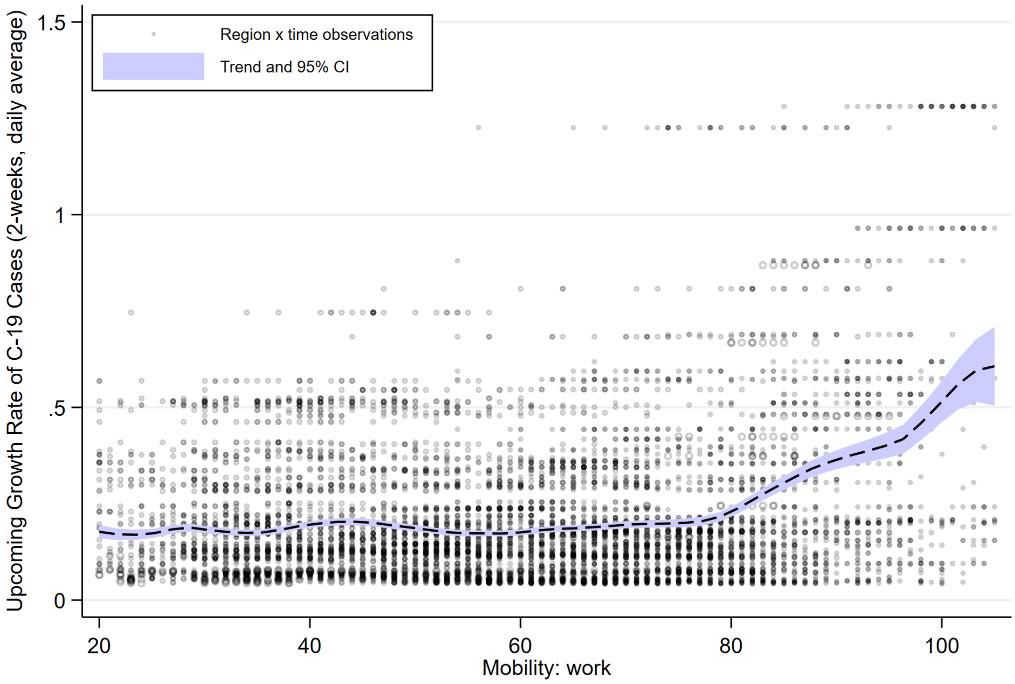


Figure 4: Effect of Mobility on Upcoming Growth Rate of COVID-19 Cases.

increase).[11]

Then, we multiply this elasticity by the mobility-poverty elasticity estimated 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, pointing to an elasticity of around 0.08. That is, a 10% (1 standard deviation) higher rate of regional poverty is associated with a 0.8% (5%) higher growth rate of COVID-19. To get a notion of how it translates in terms of number of cases, note that there were 190 cumulated cases on average in the countries of our sample by March 20th and around 22,500 cases on average by May 3 (ECDC figures). Using the estimated elasticity, we find that a one-standard deviation difference in poverty between two regions correspond to a difference of 11% on May 3 (around 2,500 cases) and 14% after two months. Robustness checks confirm these orders of magnitude.[12]

[11]This elasticity is 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) point to an impact of the reduction in human mobility on the infection growth rate. They 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.

[12]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.

4 Conclusion

While staying at home helps to slow the spread of the COVID-19 virus, social distancing can carry a high cost in poorer regions of the world where people typically have little savings, low food stocks and depend heavily on casual labor to cover basic needs for survival. As a result, poor people are more likely to show lower compliance with self-isolation requirements by continuing daily labor activities to feed themselves and their families. Using daily mobility data for 9 African and Latin American countries, we show that regions with higher poverty rates are associated with a smaller decrease in work-related mobility upon the announcement of national confinement measures in March 2020. A one standard-deviation increase in regional poverty rate – equivalent to moving from low to high poverty regions within a country – leads to 11% more COVID-19 cases by early May on average through the channel of higher work mobility.

Thus, lockdowns without support are significantly less likely to elicit broad compliance and can have serious consequences for poor people. Governments in low-income countries must accompany stringent lockdown policies with appropriate support in the form of combined healthcare efforts and consumption support, either through transfers in cash if food markets are working or in kind if they are not (Ravallion, 2020). A consideration for pursuing targeted cash transfers to deal with COVID-19 is whether they can fit in with the delivery system of existing transfer schemes and whether the latter have proven to be effective (Beegle et al., 2018, Gentilini, 2020). It is also possible to rapidly scale up existing schemes through temporary modifications such as removing work or school-attendance requirements (which run counter to the need to slow the spread of the virus). If no effective pre-existing system is in place for household targeting, other schemes can be considered including the use of geographical targeting based on poverty maps and epidemiological/containment maps (McBride and Nichols, 2018).

Several research paths are suggested. First, while current policy action is monitored in real time (Gentilini et al., 2020), future research should investigate whether social assistance provided by governments helps to ensure a desired level of public compliance with self-isolation requirements during pandemic. Second, even though the penetration rate of mobile phones is now high in Latin America and Africa, as discussed above, some corrections could be brought to our measures for imputation of daily mobility changes in nationally representative surveys (Wesolowski et al., 2012, Pokhriyal and Jacques, 2017, Steele et al., 2017, Blumenstock et al., 2015). Finally, similar methodologies could be applied to other parts of the world – in particular in India where the human cost of lockdown may be huge given that a quarter of the population make their major living from casual occupations (Ray et al., 2020). In this context, the expertise of geographers using social network data could help to correlate mobility with poverty at a more disaggregated level than we could.[13]

[13] https://theconversation.com/mapping-the-lockdown-effects-in-india-how-geographers-can-contribute-to-tackle-covid-19-diffusion-136323

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Appendix

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 Contínua) / 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 consumption	National moderate (extreme) poverty line: 5.95/3.16 [5.5/1.9]	https://www.inei.gob.pe/estadisticas/indice-tematico/sociales/ (Población con al menos una 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.1: List of Sources of Regional Poverty Data

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

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

Table A.3: Mobile Phone Penetration Rates

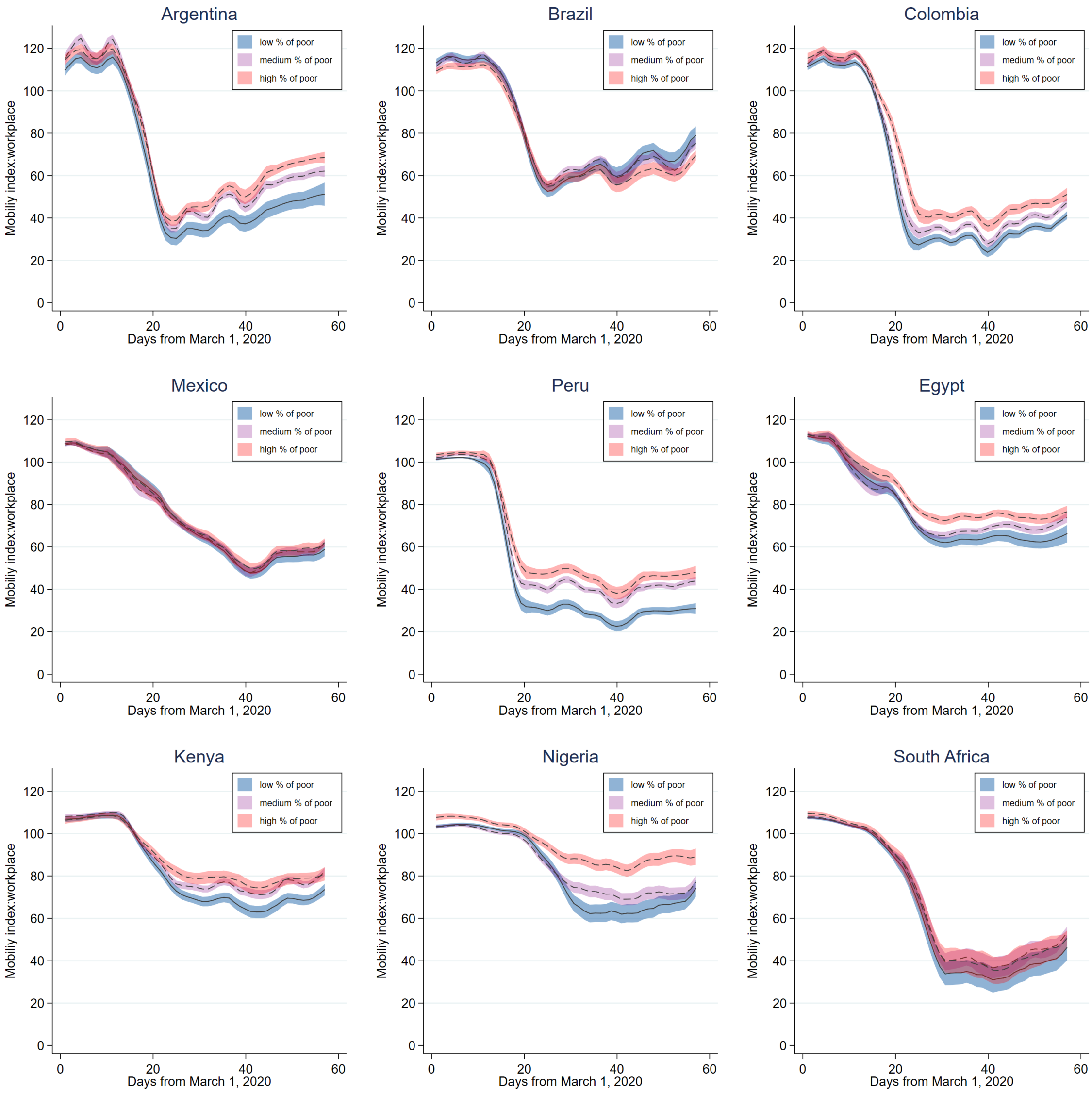
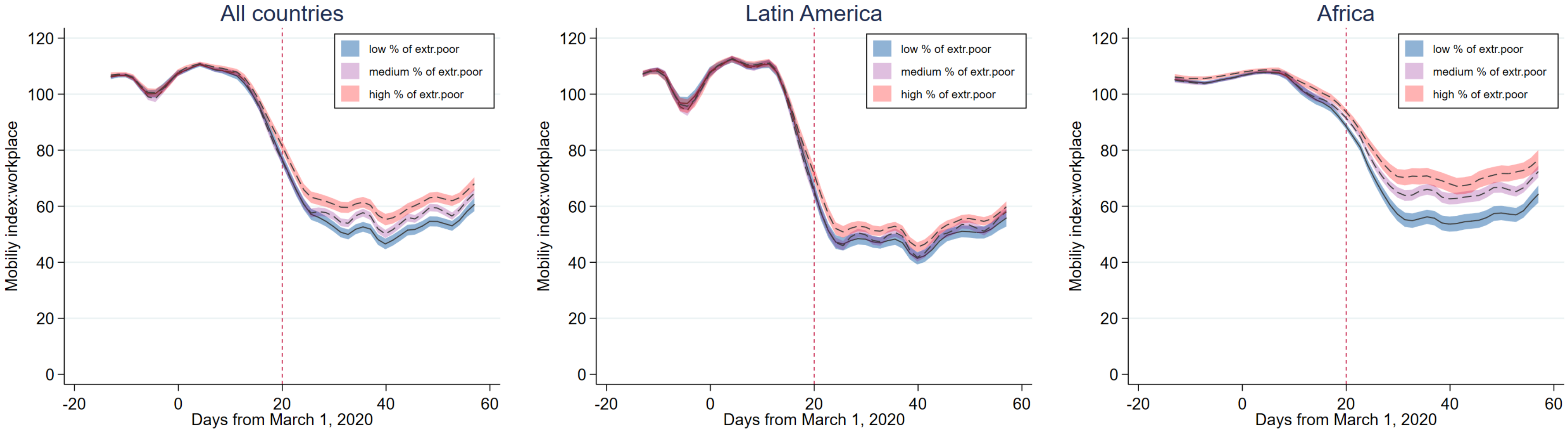


Figure A.1: Work Mobility by Regional Poverty Levels (All Countries).



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.

Figure A.2: Mobility to Workplaces by Levels of Extreme Poverty.

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