THE IMPACT OF COVID-19 AND EXPANDED SOCIAL ASSISTANCE ON INEQUALITY AND POVERTY IN ARGENTINA, BRAZIL, COLOMBIA AND MEXICO

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COMMITMENT TO EQUITY

CEQ INSTITUTE
COMMITMENT TO EQUITY
Tulane University

Working Paper 92
August 2020
(Revised June 2021)

The CEQ Working Paper Series

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ABSTRACT

Based on the economic sector in which household members work, we use microsimulation to estimate the distributional consequences of COVID-19-induced lockdown policies in Argentina, Brazil, Colombia and Mexico. Our estimates of the poverty consequences are worse than many others' projections because we do not assume that the income losses are proportionally equal across the income distribution. We also simulate the effects of most of the expanded social assistance governments have introduced in response to the crisis. This has a very large offsetting effect in Brazil, a significant effect in Argentina, and smaller in Colombia. In Mexico, there has been no such expansion. Contrary to prior expectations, we find that the worst effects are not on the poorest, but those (roughly) in the middle of the *ex ante* income distribution. In Brazil, we find that poverty among the afrodescendants and indigenous populations increases by more than for whites, but the offsetting effects of expanded social assistance also are larger for the former. In Mexico, the crisis induces a significantly less increase in poverty among the indigenous population than it does for the nonindigenous one. In all countries, the increase in poverty induced by the lockdown is similar for male- and female-headed households, but the offsetting effect of expanded social assistance is greater for female-headed households.

JEL Codes: C63, D31, I32, I38

Keywords: COVID-19, inequality, poverty, mobility, microsimulations, Latin America

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* This paper was prepared as part of the Commitment to Equity Institute's country-cases research program and benefitted from the generous support of the Bill & Melinda Gates Foundation. For more details, click here www.ceqinstitute.org. The authors are very grateful to François Bourguignon, Raymundo Campos, Mercedes D'Alessandro and colleagues in Argentina's Ministry of Economy, Cristina Fernandez, Carlos Grushka, Daniel Heymann, Rafael Rofman, John Scott, Sergei Soares, and Mariano Tommasi, and anonymous peer-reviewers from CEPR's COVID Economics and CGD's Working Papers Series. We are particularly grateful to the peer-reviewers of World Development for their very useful comments and suggestions. We also thank participants of the CEQI-CEDH/Universidad de San Andres-Poverty Global Practice/World Bank seminar "Estimating Poverty and Equity Impact of COVID-19 in Argentina: a Microsimulation Approach" (July 10th, 2020) for their invaluable comments and suggestions. All errors remain our sole responsibility.

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The Impact of COVID-19 and Expanded Social Assistance on Inequality and Poverty in Argentina, Brazil, Colombia and Mexico [‡]

Nora Lustig, Valentina Martinez Pabon, Federico Sanz and Stephen D. Younger[§]

ABSTRACT. Based on the economic sector in which household members work, we use microsimulation to estimate the distributional consequences of COVID-19-induced lockdown policies in Argentina, Brazil, Colombia and Mexico. Our estimates of the poverty consequences are worse than many others' projections because we do not assume that the income losses are proportionally equal across the income distribution. We also simulate the effects of most of the expanded social assistance governments have introduced in response to the crisis. This has a very large offsetting effect in Brazil, a significant effect in Argentina, and smaller in Colombia. In Mexico, there has been no such expansion. Contrary to prior expectations, we find that the worst effects are not on the poorest, but those (roughly) in the middle of the *ex ante* income distribution. In Brazil, we find that poverty among the afrodescendants and indigenous populations increases by more than for whites, but the offsetting effects of expanded social assistance also are larger for the former. In Mexico, the crisis induces a significantly less increase in poverty among the indigenous population than it does for the nonindigenous one. In all countries, the increase in poverty induced by the lockdown is similar for male- and female-headed households, but the offsetting effect of expanded social assistance is greater for female-headed households.

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I. Introduction

The recent COVID-19 pandemic has come at overwhelming health and economic costs to Latin America. By the end of 2020, Argentina, Brazil, Colombia, Mexico, and Peru were among the top twenty countries in terms of infections; Brazil, Mexico, and Peru were among the top ten in terms of deaths per hundred thousand inhabitants.[1] To contain the spread of the virus, governments implemented lockdown policies of various degrees.[2] Inevitably, these measures combined with the supply and demand disruptions associated with the pandemic caused a sharp reduction of activity, a fall in employment and income, and a rise in poverty and inequality.[3] In this paper we analyze the impact of the COVID-19 economic shock on inequality and poverty in 2020 in the four largest countries in Latin America: Argentina, Brazil, Colombia and Mexico.[4] In addition to lockdowns to control infection rates, governments have introduced new or expanded social assistance measures to varying degrees. We assess the extent to which these measures offset the negative effects of the lockdowns.

Based on the economic sector in which household members work, we use microsimulation to estimate potential income losses at the household level for 2020 using microdata from household surveys. The simulations first identify individuals whose income is "at risk" because they work in sectors where the lockdowns reduced or eliminated activity. We aggregate this at-risk income to the household level and then simulate actual losses using a range of two key parameters: the share of households with at-risk income that actually lose income and, of those who lose income, the share of at-risk income lost. We allow both parameters to range from zero to one hundred percent, yielding a range of possible outcomes. We select the most plausible scenario using the following criteria. For macroeconomic consistency, we choose the scenario for which the decline in per capita gross income comes closest to the figures in the IMF World Economic Outlook from April 2021.[5] There are several combinations of the two parameters that would be consistent with the overall macroeconomic contraction. We present results for the one for which the share of households that lose income comes closest to the available information from the World Bank's High-Frequency Monitoring Dashboard and other sources. Other cases leading to a similar decline in per capita income but different combinations of the two key parameters are available in the appendix for sensitivity analysis.

To complete the analysis, we construct a simulated income distribution that incorporates the losses we estimate and compare it with the *ex ante* distribution. We also simulate a third distribution that

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[1] https://coronavirus.jhu.edu/data/mortality
[2] For a description of lockdowns by country see, for example, Pages et al. (2020).
[3] According to IMF (2021) and ECLAC (2021), the region's GDP could contract in 2020 by 7.0 and 7.7 percent, respectively.
[4] Note that mobility here refers to *ex ante*/*ex post* comparisons and not to mobility over time or intergenerational mobility.
[5] We use the IMF predictions for 2020 adjusted to per capita growth rates using data on population growth for latest year available. Then, following the method suggested by Ravallion (2003) and applied by Lackner et al. (2020), we assume a "pass-through" of GDP growth to household (gross) income growth of 0.85.

incorporates the effects of the lockdown plus any new compensatory social assistance measures each government has taken. In addition to comparing standard distributional statistics for each income distribution, we find it especially useful to examine income losses conditional on one's position in the *ex ante* distribution.[6]

In addition to the obvious observation that the impact of the crisis is huge by any standard, our approach yields four important conclusions. First, increases in poverty are worse than if we had assumed that each household's income declines by an equal proportion as many other studies do as shown below. This is a convenient assumption for the rapid analysis the crisis demands, and a necessary one for those working only with macroeconomic data, but it is inaccurate. Second, contrary to many people's priors, the non-anonymous growth incidence curves show that the losses are greatest in the middle (roughly) of the *ex ante* distribution rather than among the poorest. This is because the social assistance policies put in place in most Latin American countries over the past 25 years (Stampini and Tornarolli, 2012) put a "floor" under the incomes of the poorest. Third, the governments that introduced substantial expansions of existing social assistance or entirely new programs such as Brazil and to a lesser extent Argentina were able to offset a significant share of the poverty caused by the crisis.

Fourth, in Brazil, we find that poverty among afrodescendants and indigenous populations increases by more than for whites, but the offsetting effects of expanded social assistance also are larger for the former. In Mexico, the crisis induces a significantly less increase in poverty among the indigenous population. In all countries, the increase in poverty induced by the lockdown is similar for male- and female-headed households, but the offsetting effect of expanded social assistance is greater for female-headed households.

This paper makes several contributions. First, on the growing literature that predicts the impact of COVID-19 on poverty, most existing exercises assume that income losses are proportional across the income distribution. For example, CONEVAL (2020) (for Mexico), Lackner et al. (2021), Sumner, Hoy, and Ortiz-Juarez (2020), and Valensisi (2020).[7] However, based on existing information, the distribution of income is changing—and changing fast--during the lockdowns. In particular, "real time" telephone surveys seem to show that it is the poorer and informal sector workers who lose employment and income in a larger proportion due to the "COVID-19 effect."[8] Our microsimulation allows us to relax the equal loss assumption and incorporate distributional changes in the analysis. In particular, we use techniques analogous to non-anonymous growth incidence curves to describe income losses across the *ex ante* income distribution. Although in Acevedo et al. (2020), Delaporte, Escobar and Peña (2020), ECLAC (2021), Solidarity Research Network (2020) (for Brazil), Universidad de los Andes (2020) (for Colombia) and Vos, Martin, and Laborde (2020) incomes do

[6] This is analogous to the non-anonymous growth incidence curves in Bourguignon (2011), albeit here describing a contraction.
[7] Decerf et al. (2020) focus on a different question but they also assume no change in the distribution of income.
[8] See, for example, Bottan, Hoffman and Vera-Cossio (2020), INEGI (2020), Universidad Iberoamericana (2020), World Bank (2020).

not contract proportionally, these studies do not provide non-anonymous analysis of income losses (income transitions or losses across the income distribution). Second, ours is among the first work to describe the distributional consequences of the expanded social assistance governments have implemented in response to the crisis and the extent to which that assistance offsets the crisis' effect on poverty. Some countries have expanded social assistance considerably in response to the crisis, so ignoring this exaggerates the recent increases in poverty. Third, we estimate the impact on living standards of the pandemic and social assistance by race and ethnicity and gender. Fourth, we propose a methodology to analyze the impact of a shock on income distribution that can be easily adapted to different countries and contexts with relatively little *ex ante* information.[9]

Our exercise has some important caveats. The microsimulations do not take into account behavioral responses or general equilibrium effects, so they yield first-order effects only. Our results depend on the specific assumptions we make about income sources that are "at risk" (which we detail in Table A2 in the Appendix). A third caveat is that our simulation of social assistance programs includes most but not all of the emergency programs implemented.

II. Data and Methodology[10]

We obtain our estimates by simulating potential income losses in 2020 at the household level using microdata from household surveys. We use the most recent household survey available in each country from before the pandemic: Argentina: Encuesta Permanente de Hogares (EPH, 2019), Brazil: Pesquisa Nacional por Amostra de Domicilios Continua (PNADC, 2019), Colombia: Gran Encuesta Integrada de Hogares (GEIH, 2019), Mexico: Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH, 2018). The household surveys for Brazil, Colombia, and Mexico are representative at the national level. In Argentina, the survey covers only urban areas that represent around 62 percent of the population. For simplicity, we will refer to "Argentina" except in tables and figures where we shall add "urban". We use gross income per capita as the welfare indicator. Gross income is defined as labor income plus rents, private transfers, pensions, and government cash transfers before any direct taxes. To maintain comparability across countries, we exclude own-consumption and the rental value of

[9] For example, Issahaku and Abu (2020), Nafula et al. (2020), Seck (2020), Yimer, Alemayehu and Taffesse (2020), and Younger et al. (2020) apply our methodology to estimate the distributional consequences of COVID-19 in Ghana, Kenya, Senegal, Ethiopia and Uganda, respectively. Results suggest that the pandemic has severe consequences on poverty and inequality, reverting any progress made during the previous years.

[10] Appendix B presents a previous version of this paper that, although similar in many ways to this version, does not incorporate the most recent information on growth projections and expanded social assistance for the entire 2020 and does not include information from high-frequency surveys. In Appendix B, due to the absence of data and a higher uncertainty behind the actual scenario of income losses, we present results for two extreme opposite situations regarding the share of households that bear the burden of losses. We call these "concentrated losses" and "dispersed losses" scenarios. The possibility of applying the methodology when different amounts of information are available underscores its advantages. We decided to publish the second exercise in Appendix B of this working paper to illustrate this point.

owner-occupied housing.[11,12] We update gross incomes for Mexico to 2019 by the GDP per capita growth rate for 2019 multiplied by a so-called pass through of 0.85.[13] Also, for Mexico, we update gross incomes to take into account the significant reforms introduced to the cash transfers system in 2019.[14]

The microsimulations identify individuals whose income is "at risk" or "not at risk" as follows. We first assume that income derived from work in sectors that are "essential" is not at risk. For Argentina and Colombia, the lockdown measures stated explicitly which sectors are essential. For Brazil and Mexico, we use the ILO definition of essential sectors.[15] The not-at-risk income category also includes incomes from cash transfers programs, social security pensions, public employment, private transfers (e.g., remittances),[16] and the income earned in "nonessential" sectors by white-collar workers who are CEO's, managers, and researchers with internet access at home.[17] The not at risk income category excludes incomes of informal street vendors regardless of the sector in which they work[18] and rental incomes; both these categories are included in the at risk income. We aggregate the not-at-risk income at the household level. The at-risk income is then obtained as the difference between the total gross household income and the total income that is not at risk.

Other studies use the ability of teleworking as a way to identify the employment/income that may not be at risk.[19] We checked the robustness of our classification method by comparing the proportion of workers that can telework using our approach with that obtained by Delaporte and Peña (2020) for Latin American countries. Our results regarding the share of workers who can work from home are

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[11] This may result in some discrepancies with poverty estimates published in national and international databases such as the World Bank's PovcalNet.

[12] For Mexico and Colombia we do have information on these two incomes. Including own-consumption has little effect on the results as this is a small amount even for the poorest. What effect there is, however, is concentrated among poorest. The rental value of owner-occupied housing reduces the share of at-risk income roughly equally across the income distribution for both countries.

[13] The use of a pass through to convert GDP changes into changes in household disposable incomes was proposed by Ravallion (2003) and is applied by Lakner et al. (2020).

[14] The reforms are briefly described in Lustig and Scott (2019); details on how this update was carried out are available upon request.

[15] Decree 297/2020 (Argentina), Decree 457 of March 22nd of 2020 (Colombia), and ILO Monitor: COVID-19 and the world of work (Brazil and Mexico). Table A2 in the appendix shows the distribution of employment between at-risk and not-at-risk by sector.

[16] Existing information suggests that international remittances in Latin America have not been negatively affected by the pandemic. In our four countries, remittances are important primarily for Mexico. Based on information from Banco de Mexico (2021), despite the crisis, income from remittances grew in 2020 compared to 2019.

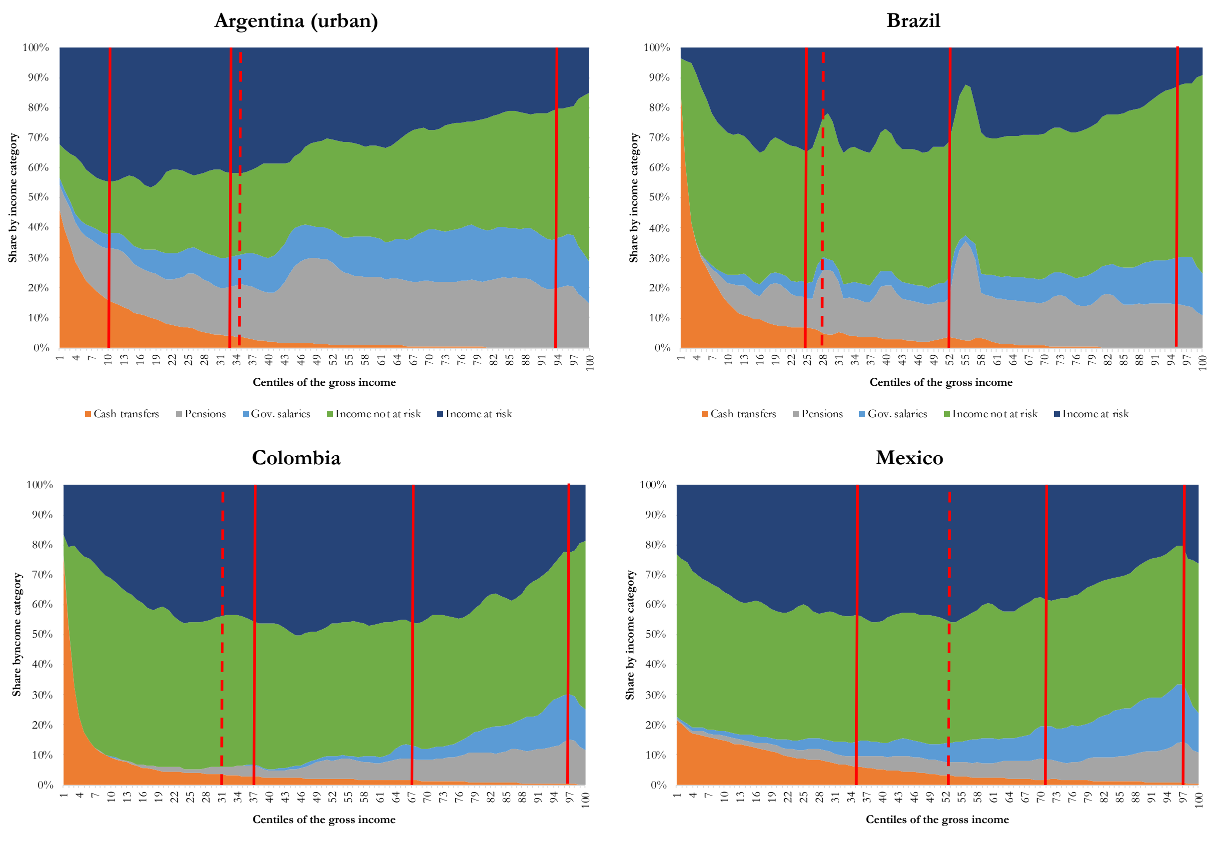
[17] In the case of Argentina, the household survey does not allow us to identify internet access at home for white-collar workers. Thus, all of these workers were considered as not having their income at risk.

[18] For all other employment, whether workers are in the formal or informal sectors does not determine whether their incomes are or not at risk.

[19] See, for example, Bartik, Cullen, Glaeser, Luca and Stanton (2020), Delaporte and Peña (2020), Dingel and Neiman (2020), Hatayama, Viollaz, and Winkler (2020), and Saltiel (2020). Dingel and Neiman (2020) is based on the task content of occupations in the US. Saltiel (2020) proposes an alternative method that adapts Dingel and Neiman (2020) for developing countries using worker-level data from the World Bank (Skills Toward Employability and Productivity survey). Delaporte and Peña (2020) indicate that Saltiel (2020) results are more appropriate to a developing country context.

similar to that obtained by the latter (when they apply Saltiel (2020) approach, the preferred one for developing countries). Furthermore, as far as we can tell, even the more appropriate approach has its limitations because not all workers who cannot telework should be assumed as having their income at risk, which seems to be the assumption in Delaporte and Peña (2020). Workers in essential sectors (healthcare, for example) will not have their incomes at risk even if they cannot telework. Thus, the approach we used here to classify incomes between at risk and not at risk appears to be more realistic because it includes the latter among the workers whose incomes are not at risk. In fact, Delaporte, Escobar, and Peña (2020) do exactly that in a subsequent article. In addition, in our definition of incomes that are not at risk we also include nonlabor income such as income received from governments (as transfers or wages), remittances, and—except for rents--incomes from capital (e.g., interests and dividends) while Delaporte, Escobar, and Peña (2020) contemplate labor income only.

Figure 1. Composition of Per Capita Household Gross Income



Notes: The dashed vertical line is the national poverty line and the bold vertical lines are—from left to right-- the $5.50 (moderate poor), $11.50 (lower-middle class) and $57.60 (middle class) per day international lines (in 2011 PPP), respectively.

Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Figure 1 shows the composition of per capita gross income by centile of the pre-crisis (December 2019) income across five categories: cash transfers, social security pensions, government salaries, incomes not-at-risk, and incomes at-risk. The first three categories are incomes that generate in the public sector. Note that the share of income that is not at risk – everything but the dark blue area – is not equal across the income distribution as many studies assume, nor is it uniformly decreasing in income as it would be if the poorest were most at risk. Rather, it is U-shaped with the greatest risk in the middle of the income distribution rather than either extreme.[20] The very poorest households have an income floor from existing targeted cash transfers (albeit low) that protects an important share of their income. The richest households also have relatively lower income at risk than the middle. In Colombia, Mexico, this is due to income from social security pensions and employment in the public sector. In Argentina and Brazil, households in the higher deciles have less of their income coming from at risk sectors.[21]

Once we identified the at-risk incomes, we proceed to simulate potential losses using a range of two key parameters: the share of households with at-risk income that actually lose income and, of those who lose income, the share of at-risk income lost. Households who lose income (from the set of households with at-risk income) are randomly selected. We allow both parameters to range from zero to one hundred percent. We subsequently aggregate the results into a ten-by-ten matrix of possible total per capita gross income losses in 10 percent intervals. Cells in Table 1 show the range of possible total (and not just the at-risk component) per capita households' gross income losses as a proportion of *ex ante* gross income as we vary both the probability that households lose at-risk income (down the rows) and the share of that at-risk income they lose (across the columns). For example, in the 10 percent-10 percent cell of this matrix we show the fall in total per capita gross income in percent corresponding to the case in which 10 percent of the households (with at risk income) lose 10 percent of their income.

Our initial results for income losses provide a wide range of possibilities from near zero to 25-over 30 percent of pre-crisis income (depending on the country). For macroeconomic consistency, we first narrow our focus to scenarios for which the decline in per capita gross income comes closest to the IMF's World Economic Outlook country growth estimates published in April 2021 (see cells highlighted in dark grey in Table 1).[22] Outcomes with income losses similar to the IMF's projections form an "iso-loss" curve that runs through each table.[23] In these iso-loss curves, the results closest to the corners represent the cases where either the smallest proportion of households lose much income (upper right) –we call this the "concentrated losses" scenario-- or the largest proportion of households lose smaller amounts of income (lower left) –"dispersed losses" scenario.

[20] Here we should note that the Argentina survey is urban only which may explain the somewhat difference shape compared to the other countries.
[21] Taking an average of the composition of gross income by decile we find that income at risk represents 26.5 percent, 20 percent, 34 percent, and 33 percent of total gross income in Argentina, Brazil, Colombia and Mexico, respectively.
[22] We use the IMF predictions for 2020 adjusted to per capita growth rates using data on population growth for latest year available. Then, following the method suggested by Ravallion (2003) and applied by Lackner et al. (2020), we assume a "pass-through" of GDP growth to household (gross) income growth of 0.85.
[23] Recall that the IMF contractions are converted into per capita changes and that we assume a 0.85 pass-through from GDP to household incomes so the figures are not identical to the IMF projections for GDP changes by definition.

In the absence of data, the concentrated and dispersed losses scenarios provide estimates for two extreme opposite situations in terms of the share of households that bear the burden of losses. Real-time telephone surveys such as the World Bank's High-Frequency Monitoring Dashboard, however, show the share of households that declare having lost income, so we are now able to choose a specific cell within the matrix. For Colombia, the World Bank (2020) shows that 71.7 percent of households experienced a decline in their total income; to estimate results, we rounded this up to 70 percent.[24] For Mexico, Universidad Iberoamericana (2021) finds that between April and December 2020, on average, 64 percent of households experienced a decrease in total income and we rounded it up to 60 percent for the selected scenario.[25] Since there is no information for Argentina and Brazil, we used 70 and 80 percent, respectively, the average for Latin America according to two major studies for the region.[26] We show the selected scenario for each country in dark grey in Table 1 and present results for the latter in the next section. Specifically, our microsimulations are based on the following scenarios. The total gross per capita income losses assumed in Argentina are 9.4 percent with 70 percent of households losing 50 percent of their income. In Brazil, 4.2 percent with 80 percent of households losing 20 percent. In Colombia, 7.1 percent with 70 percent of households losing 30 percent. In Mexico, 7.9 percent with 60 percent of households losing 40 percent. Alternative scenarios yielding a similar aggregate decline in per capita gross income (the light grey highlighted cells) but different combinations of the two key parameters are available in the appendix.

Table 1. Income Losses Matrix (as % of total gross income)
Panel (a) Argentina (urban)

% households losing income \ % of income lost	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.3	0.5	0.8	1.1	1.3	1.6	1.9	2.1	2.4	2.7
20%	0.5	1.0	1.6	2.1	2.6	3.1	3.6	4.2	4.7	5.2
30%	0.8	1.6	2.4	3.2	4.0	4.8	5.6	6.4	7.2	8.0
40%	1.0	2.1	3.1	4.2	5.2	6.3	7.3	8.3	9.4	10.4
50%	1.3	2.6	3.9	5.2	6.5	7.8	9.1	10.4	11.7	13.0
60%	1.6	3.1	4.7	6.2	7.8	9.3	10.9	12.4	14.0	15.5
70%	1.8	3.7	5.5	7.3	9.2	11.0	12.8	14.7	16.5	18.3
80%	2.1	4.2	6.3	8.4	10.5	12.6	14.7	16.8	18.9	21.0
90%	2.4	4.8	7.1	9.5	11.9	14.3	16.7	19.0	21.4	23.8
100%	2.6	5.3	7.9	10.6	13.2	15.9	18.5	21.1	23.8	26.4

24 Using a different indicator, Bottan, Hoffmann, and Vera-Cossio (2020) show that almost 80 percent of households reported loss of livelihood.

25 Bottan, Hoffmann, and Vera-Cossio (2020) show that approximately 70 percent of households reported loss of livelihood.

26 The World Bank (2020) shows that in 2020 the share of households that experienced a decline in total income is 67.6 percent, on average, for Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Honduras, Paraguay, and Peru. Bottan, Hoffmann, and Vera-Cossio (2020) find that, on average, for a sample of seventeen countries from Latin America and the Caribbean, over 70 percent of respondents to an online/telephone survey conducted during 2020 reported decreases in income.

Panel (b) Brazil

% households losing income \ % of income lost	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.3	0.5	0.8	1.1	1.3	1.6	1.8	2.1	2.4	2.6
20%	0.5	1.1	1.6	2.1	2.7	3.2	3.7	4.3	4.8	5.4
30%	0.8	1.6	2.4	3.2	4.1	4.9	5.7	6.5	7.3	8.1
40%	1.1	2.2	3.2	4.3	5.4	6.5	7.5	8.6	9.7	10.8
50%	1.3	2.7	4.0	5.4	6.7	8.1	9.4	10.7	12.1	13.4
60%	1.6	3.2	4.8	6.4	8.1	9.7	11.3	12.9	14.5	16.1
70%	1.9	3.8	5.6	7.5	9.4	11.3	13.2	15.0	16.9	18.8
80%	2.2	4.3	6.5	8.6	10.8	12.9	15.1	17.3	19.4	21.6
90%	2.4	4.8	7.3	9.7	12.1	14.5	17.0	19.4	21.8	24.2
100%	2.7	5.4	8.1	10.8	13.5	16.2	18.9	21.6	24.3	27.0

Panel (c) Colombia

% households losing income \ % of income lost	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.3	0.7	1.0	1.4	1.7	2.0	2.4	2.7	3.1	3.4
20%	0.7	1.3	2.0	2.6	3.3	3.9	4.6	5.2	5.9	6.6
30%	1.0	2.0	2.9	3.9	4.9	5.9	6.9	7.8	8.8	9.8
40%	1.3	2.6	4.0	5.3	6.6	7.9	9.2	10.5	11.9	13.2
50%	1.7	3.3	5.0	6.6	8.3	9.9	11.6	13.3	14.9	16.6
60%	2.0	4.0	6.0	8.0	10.0	12.0	13.9	15.9	17.9	19.9
70%	2.3	4.7	7.0	9.4	11.7	14.0	16.4	18.7	21.1	23.4
80%	2.7	5.3	8.0	10.7	13.4	16.0	18.7	21.4	24.0	26.7
90%	3.0	6.0	9.0	12.0	15.0	18.0	21.1	24.1	27.1	30.1
100%	3.4	6.8	10.2	13.6	17.0	20.4	23.8	27.2	30.6	34.0

Panel (d) Mexico

% households losing income \ % of income lost	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.3	0.6	1.0	1.3	1.6	1.9	2.3	2.6	2.9	3.2
20%	0.6	1.3	1.9	2.6	3.2	3.9	4.5	5.2	5.8	6.4
30%	1.0	1.9	2.9	3.9	4.9	5.8	6.8	7.8	8.7	9.7
40%	1.3	2.6	3.9	5.2	6.5	7.8	9.1	10.4	11.7	13.0
50%	1.6	3.3	4.9	6.5	8.1	9.8	11.4	13.0	14.6	16.3
60%	2.0	3.9	5.9	7.8	9.8	11.8	13.7	15.7	17.7	19.6
70%	2.3	4.6	6.9	9.1	11.4	13.7	16.0	18.3	20.6	22.8
80%	2.6	5.2	7.8	10.5	13.1	15.7	18.3	20.9	23.5	26.1
90%	2.9	5.9	8.8	11.7	14.7	17.6	20.5	23.5	26.4	29.3
100%	3.3	6.6	9.9	13.1	16.4	19.7	23.0	26.3	29.6	32.8

Notes: Highlighted cells correspond to losses similar to the loss projections by IMF (2021). The dark grey is the scenario where in addition to macroeconomic consistency, the share of households that have reported losing income corresponds to the available information.

Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

In addition to examining the *ex ante* and *ex post* income distributions, we construct a third distribution that simulates most of the additional policies each government has put in place to cushion the impact of the crisis, including both expansions of existing social assistance and introduction of new programs. This yields an *ex post*, post-policy response distribution. Table 2 gives a brief description of each government's policy responses in 2020 incorporated in our simulations of emergency social assistance programs.[27] Note that Mexico has provided no additional social assistance (at the federal level) in the wake of the crisis.[28]

For simulating the expanded social assistance, we proceeded as follows. In the case of programs that existed pre-COVID, we assigned the post-COVID additional payments to the households in which household members in the survey reported being beneficiaries of the existing pre-COVID programs. For the new social assistance programs, we first identify possible beneficiary households based on the definition of each program's target population (e.g., informal workers, female household head, socio-economic level, and so on) and then assign the transfer randomly but only among the target population to match the number of total beneficiaries in the survey to that reported in the administrative data.[29]

Table 2. COVID-19 New and Expanded Social Assistance Included in Simulations

Country	Program	Target population of new programs	Number of transfers	Amount of the transfers		Transfer as % of poverty lines		Total beneficiaries by the end of the year (administrative data)	Fiscal cost as % of GDP
				LCU	USD	National	$5.50 PPP		
Argentina	Ingreso Familiar de Emergencia*	Vulnerable, Informal workers	3	ARG$10,000	US$148	113.5	253.3	9 million people	1.41%
	AUH / AUE	-	1	ARG$3,100	US$46	35.2	78.5	4.3 million people	0.07%
								memo: Total	1.48%
Brazil	Auxílio Emergencial*	Vulnerable, Informal workers	9	R$300-R$600	US$53-US$107	121.9	140.3	67 million people	3.32%
								memo: Total	3.32%
Colombia	Ingreso solidario*	Vulnerable, Informal workers	9	COL$160,000	US$42	65.9	58.8	3 million households	0.44%
	Bogotá solidaria*	Vulnerable, Informal workers	5	COL$233,000	US$60	95.9	85.6	521 thousand households	0.06%
	Familias en Acción	-	5	COL$145,000	US$38	59.7	53.2	2.6 million households	0.19%
	Jóvenes en Acción	-	5	COL$356,000	US$92	146.5	130.7	204 thousand people	0.04%
	Colombia Mayor	-	5	COL$160,000	US$42	65.9	58.8	1.7 million people	0.14%
								memo: Total	0.87%
Mexico	No additional social assistance								

Notes: * refers to new social assistance programs that were introduced in the first months of lockdowns. For a more detailed description (and sources) see Table A1 in the Appendix. Amount of the transfer in (LCU/USD) prices of May 2020. The number of beneficiaries in the simulations do not necessarily correspond exactly to those shown above because in Argentina the simulations apply to urban areas only. The numerator of the fiscal cost is

27 We do not include employment support programs. Their impact is implicit in the projected aggregate contraction in the sense that the income of the beneficiary households of these programs is not at risk. In order to estimate the benefit of this policy, proper pre-policy counterfactuals need to be generated, which is beyond the scope of this paper. Thus, the contribution of government policies to mitigate the impact of the pandemic presented here may be a closer to a lower bound. For a more comprehensive description of programs that were introduced by the governments in the four countries examined here, see Blofield, Lustig and Trasberg (2020).

28 Mexico neither expanded nor introduced new safety nets. There were really only two mitigation policies and neither involves an additional transfer: beneficiaries of the noncontributory pensions and scholarships were given two months in advance (with total payments for the year unchanged, at least for now) and access to "credito a la palabra" (a loan without any guarantees) to mainly small and medium enterprises (which could become a transfer in retrospect if they are not paid back).

29 For a more detailed description of the existing and new programs included in the simulations, see Table A1 in the Appendix.

obtained by multiplying the size of the transfers by the number of times it was given and the number of beneficiaries; the denominator equals GDP per IMF projections for 2020 (IMF, 2021).

III. Results

1. Impact on inequality and poverty[30]

As mentioned in the Introduction, compared with some of the other existing studies, ours does not assume that all incomes change in the same proportion. In other words, from the outset, we consider that the pandemic will have differential effects depending on the sources of income and the ability to telework. Indeed, as shown in Table 3 inequality (measured with the Gini coefficient) and before considering the impact of the expanded social assistance, increases in the four countries.[31] See the change in Gini points under the heading "without expanded social assistance." With the expansion of existing and new social assistance, the remarkable result is that inequality in Brazil is lower than in the prepandemic. In Argentina, the unequalizing effect appears to have been mitigated substantially: the 2.6 increase in Gini points without expanded social assistance falls to 0.9. The mitigating effect is smaller in Colombia. Since Mexico did not expand the social assistance, inequality there is expected to rise by the most.

Table 3. Gini Coefficient

		Without Expanded Social Assistance		With Expanded Social Assistance	
Country	Gini Coefficient *Ex ante*	Gini Coefficient *Ex post*	Change (Gini points)	Gini Coefficient *Ex post* + Social Assistance	Change (Gini points)
Argentina (urban)	44.4	47.0	2.6	45.3	0.9
Brazil	55.4	56.1	0.8	52.5	-2.9
Colombia	55.0	56.2	1.2	55.1	0.1
Mexico	46.4	47.9	1.5		

Note: Change is the difference between *ex post* and *ex ante* Gini coefficients.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

The combination of severe contractions in per capita GDP with higher levels of inequality is expected to generate a more severe impact on poverty than if one assumes that all incomes fall proportionately. Table 4 shows the impact of COVID-19 and the expanded social assistance on poverty in 2020 obtained from the selected scenario for each country (see Table 1). We use two poverty thresholds: the national poverty lines and the US$5.50 a day international poverty line

[30] Estimates of inequality and poverty for cases leading to a similar decline in per capita income but different combinations of the two key parameters are available in tables A3 and A4 in the appendix.
[31] These results correspond to the selected scenario for each country as described in section 2.

(in 2011 purchasing power parity).[32,33] We present two poverty indicators: the headcount ratio and the number of new poor. Results for the squared poverty gap are shown in Table A5 in the Appendix. To assess the impact of COVID-19 and the expanded social assistance, we need to compare the *ex ante* (prepandemic) with the *ex post* (postpandemic) poverty both without and with social assistance. A first result to note is that, unsurprisingly, the increases in poverty without social assistance due to the pandemic are very large for all countries.[34] Second, in Brazil, where the government committed significant resources (3.3 percent of GDP) to expand its social assistance, policies more than offset the COVID-19-induced increase in poverty to such an extent that poverty was lower than its prepandemic levels. In Argentina and Colombia, governments dedicated less fiscal resources to new social assistance spending, so the mitigating effect is smaller. Finally, Mexico is the country where poverty rises the most and no additional resources were allocated to social assistance at the federal level, so the COVID-19 income shock was not mitigated.[35]

Table 4. Incidence of Poverty

		Without Expanded Social Assistance			With Expanded Social Assistance		
Country	Headcount ratio *Ex ante* (%)	Headcount ratio *Ex post* (%)	Change (pp.)	New poor (in millions)	Headcount ratio *Ex post* + Social Assistance (%)	Change (pp.)	New poor (in millions)
Panel (a) National Poverty Line							
Argentina (urban)	35.5	43.0	7.4	2.1	40.7	5.2	1.5
Brazil	28.2	31.0	2.9	6.0	24.9	-3.3	-6.8
Colombia	31.8	36.4	4.6	2.3	34.1	2.3	1.1
Mexico	53.8	59.3	5.5	6.9			
Panel (b) $5.5 PPP Poverty Line							
Argentina (urban)	10.9	16.5	5.6	1.6	13.0	2.1	0.6
Brazil	25.4	27.6	2.2	4.6	20.6	-4.7	-9.9
Colombia	37.6	42.1	4.5	2.2	40.3	2.7	1.3
Mexico	34.9	41.6	6.7	8.4			

Notes: Change is the difference between *ex post* and *ex ante* headcount ratios. The number of new poor is calculated as the change in *ex post* and *ex ante* headcount ratios times the projected population for 2020 obtained from the World Bank World Development Indicators. pp: percentage points.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

[32] The national poverty line in 2011 PPP a day is equivalent to $12.3 in Argentina, $6.3 in Brazil, $4.9 in Colombia, and $7.8 in Mexico.
[33] For Argentina, the conversion to 2011 PPP uses Buenos Aires city's CPI because the one produced by the National Statistics Institute (INDEC) went through a series of methodological changes that weakened its credibility. See, for example, Cavallo (2013).
[34] As a check on the importance of the assumptions we have made about which income is at-risk, we repeated our analysis assuming that *all* income (except for income from cash transfers, pensions and government salaries) is at-risk. We find the results to be broadly similar, though the increases in poverty and inequality are slightly less when we restrict our attention to outcomes with income losses similar in scale to the IMF's predictions for declines in GDP.
[35] As a check on the importance of including the change in the distribution of income on our poverty estimates, we repeated our analysis assuming that everybody's income declines by the same per capita fall projected by the IMF for each country. In this case, the increase in the number of poor in the four countries taken together would equal 9.3 million (using the $5.50 poverty line).

How do our simulations compare with other studies? At the time of the writing of this article, there are no comparable studies regarding the impact of COVID-19 on inequality. ECLAC (2021), for example, reports the Gini coefficient for the region but not for individual countries. Delaporte, Escobar, and Peña (2020) present results for individual countries but their study focuses on the initial phase of the lockdown while ours considers the contraction for the entire year of 2020; furthermore, this study does not take into account the impact of expanded social assistance. Although by now there are quite a few studies on the poverty impact of the COVID-19 crisis, several assume that losses are proportional across the income distribution so they are not useful for comparison purposes.[36] Studies that do let the income distribution change include, for example, Acevedo et al. (2020), Delaporte, Escobar and Peña (2020), and ECLAC (2021).[37] Using the $5 poverty line, Acevedo et al. (2020) estimate an increase in 17 million poor people in the four countries we analyze—almost identical to ours before considering social assistance.[38] For the four countries included here and using national poverty lines, ECLAC (2021) projects an increase of 28.3 million poor people before social assistance and 17 million poor people after social assistance. Our estimate is an increase of 17.2 million before social assistance and 9.5 million after social assistance, considerably lower. ECLAC's results are based on projections of contractions on GDP much larger than ours for Argentina, Brazil, and Mexico, a factor that may underlie their more pessimistic predictions.

The only country with poverty estimates based on actual household surveys for 2020 is Argentina. INDEC (2021a) estimates a headcount of 40.9 percent in the first semester of 2020 and 42 percent in the second semester of 2020, which is almost identical to the poverty impact resulting from our simulation exercise.

2. Poverty Impact by Ethnicity, Race and Gender

Table 5 presents results for the change in poverty across distributions by race in Brazil and ethnicity in Mexico.[39] In Brazil, the impact of the lockdown on afrodescendants and indigenous populations is more severe than for whites. At the same time, the newly introduced social assistance offsets more of the poverty increase for afrodescendants and indigenous populations.

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[36] For example, Sumner, Hoy and Ortiz-Juarez (2020) use the World Bank's Povcal.Net platform and generate new poverty estimates (without incorporating the effect of new or extended social assistance) by assuming that the poverty line increases by the same amount as their assumed contractions in income. CONEVAL (2020) generates poverty estimates for Mexico by assuming an aggregate contraction of 5 percent. Valensisi (2020) and Lackner et al. (2021) do not present results for individual countries.

[37] Delaporte, Escobar and Peña (2020) use the $1.90 poverty line which is not really relevant for middle-income Latin America (especially for our sample of four upper-middle income countries) and only focused on the first phase of lockdowns and do not incorporate the impact of the expansion of social assistance. Thus, their results are not comparable to ours, so we do not include them here. Solidarity Research Network (2020) and Universidad de los Andes (2020) present country-specific estimates for Brazil and Colombia, respectively. Their estimates are only focused on the first months of the pandemic, so we do not include their study here. Vos, Martin, and Laborde (2020) do not present results for individual countries.

[38] Their simulation of the effect of COVID-19 on incomes are based on the elasticity of wages to GDP by income groups.

[39] These distinctions are not possible in the data from Colombia and Argentina.

In Mexico, the impact of the lockdown is lower for indigenous people than for whites. Do these results mean that afrodescendants in Brazil have a higher share of at-risk income than whites and that the opposite occurs in Mexico? The afrodescendants and whites in Brazil have, respectively, 24.1 and 19.3 percent and the indigenous population and whites in Mexico, 34.7 and 32.8 percent. Thus, in both countries, the nonwhite populations have a higher share of income at risk, albeit in both cases the difference is small (smaller in Mexico). Therefore, the impact on the postpandemic headcount ratio being higher for nonwhites in Brazil and lower for the indigenous population in Mexico must be driven by the prepandemic relative sizes of individuals above the poverty line and the number of them who "migrate" to incomes below the poverty lines after the pandemic hits.

Table 5. Headcount Estimates by Ethnicity and Race of the Household Head

	White					Afrodescendants and indigenous				
Country	Headcount ratio *Ex ante* (%)	Headcount ratio *Ex post* (%)	Change (pp.)	Headcount ratio *Ex post* + Social Assistance (%)	Change (pp.)	Headcount ratio *Ex ante* (%)	Headcount ratio *Ex post* (%)	Change (pp.)	Headcount ratio *Ex post* + Social Assistance (%)	Change (pp.)
Panel (a) National Poverty Line										
Brazil	27.2	30.0	2.7	24.1	-3.1	35.2	38.9	3.7	31.0	-4.3
Mexico	51.7	57.3	5.6			77.2	80.3	3.0		
Panel (b) $5.5 PPP Poverty Line										
Brazil	24.6	26.7	2.1	20.0	-4.6	31.1	34.2	3.1	25.4	-5.7
Mexico	32.1	39.0	6.8			66.0	69.4	3.4		

Notes: In Brazil, the afrodescendants and indigenous populations category includes individuals who self-reported as "black" and "indigenous." In Mexico, the category only includes those individuals who responded that they speak an indigenous language. Change is the difference between *ex post* and *ex ante* headcount ratios. pp: percentage points.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table 6 presents results for the change in poverty across distributions for male- and female-headed households. The increase in poverty caused by the lockdowns is broadly similar. Only in Argentina the difference is greater than one percentage point, and that only for the national poverty line. In Argentina and Brazil, the poverty increases from the *ex ante* to the *ex post* with expanded social assistance distribution is less in female-headed households, reflecting the emphasis these countries have placed on targeting the new social assistance introduced in response to the crisis to favor female-headed households. An important caveat is in order. The gender-sensitive results presented here consider the gender of the head of household only. The relatively favorable outcome for female-headed households should not be extrapolated for women in general. There is evidence that sectors that are intensive in employing women were more severely affected and unemployment rates have increased more for female workers than for male workers in the countries where data exists.[40]

[40] See DANE (2021) for Colombia, INDEC (2021b) for Argentina, and INEGI (2021) for Mexico.

Table 6. Headcount Estimates by Sex of the Household Head

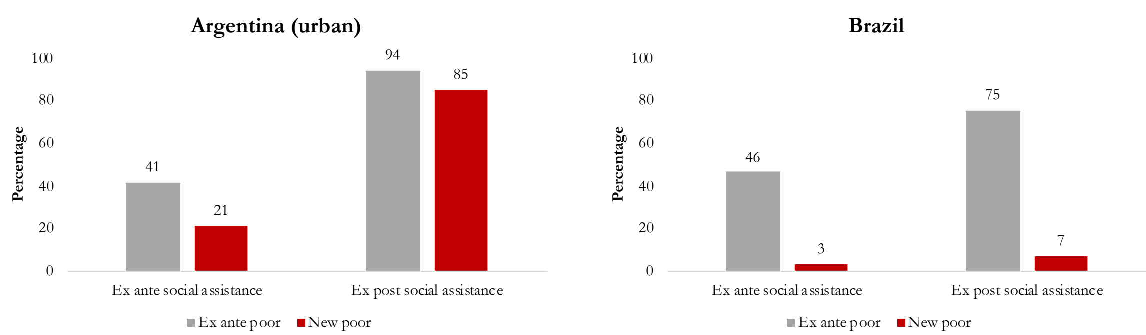
	Men					Women				
Country	Headcount ratio *Ex ante* (%)	Headcount ratio *Ex post* (%)	Change (pp.)	Headcount ratio *Ex post* + Social Assistance (%)	Change (pp.)	Headcount ratio *Ex ante* (%)	Headcount ratio *Ex post* (%)	Change (pp.)	Headcount ratio *Ex post* + Social Assistance (%)	Change (pp.)
Panel (a) National Poverty Line										
Argentina (urban)	33.6	41.3	7.7	39.3	5.7	38.7	45.4	6.6	43.1	4.3
Brazil	25.2	27.8	2.6	22.8	-2.5	31.4	34.5	3.1	27.3	-4.1
Colombia	30.1	34.7	4.6	32.5	2.5	34.9	39.6	4.7	36.9	2.0
Mexico	54.1	59.7	5.6			52.7	57.6	4.9		
Panel (b) $5.5 PPP Poverty Line										
Argentina (urban)	9.2	15.0	5.7	11.4	2.2	13.7	18.9	5.2	15.5	1.9
Brazil	22.7	24.7	2.0	18.9	-3.8	28.2	30.7	2.5	22.5	-5.7
Colombia	37.0	41.3	4.3	39.8	2.8	38.7	43.6	4.9	41.2	2.5
Mexico	35.6	42.3	6.7			32.6	38.8	6.3		

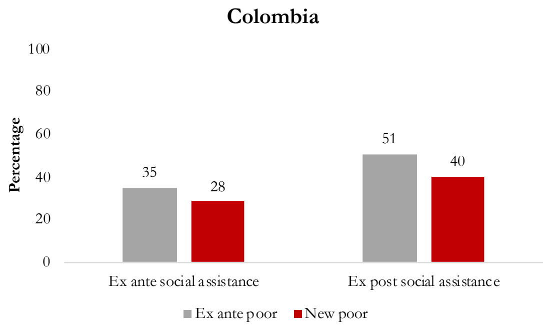
Note: Change is the difference between *ex post* and *ex ante* headcount ratios. pp: percentage points.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

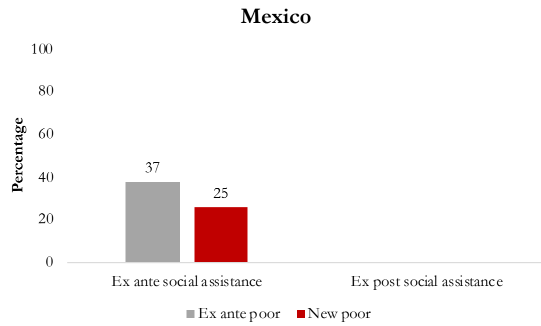
3. Coverage of Social Assistance

Figure 2 shows the coverage of social assistance transfers that existed before the crisis (on the left of each figure) and those measures plus any new or expanded social assistance implemented in response (on the right) for those who were poor before the crisis (in grey) and for those who became poor after the lockdown (in red). Argentina, Brazil, and Colombia more moderately, show increases in coverage for both the *ex ante* poor and the new poor which helps to explain their success at offsetting the poverty increase that lockdowns caused. It is also interesting that in Argentina and Colombia the coverage of the *ex ante* social assistance measures is much higher for the *ex ante* poor, as it should be, but the difference narrows once the new policies are added to the mix, also as it should. These results suggest good targeting of both *ex ante* and new social assistance measures in Argentina and Colombia. In Brazil, the impressive coverage of *ex post* social assistance offset the COVID-19-induced increase in poverty and leave the country with a small percentage of new poor.

Figure 2. Coverage of Existing and New or Expanded Social Assistance







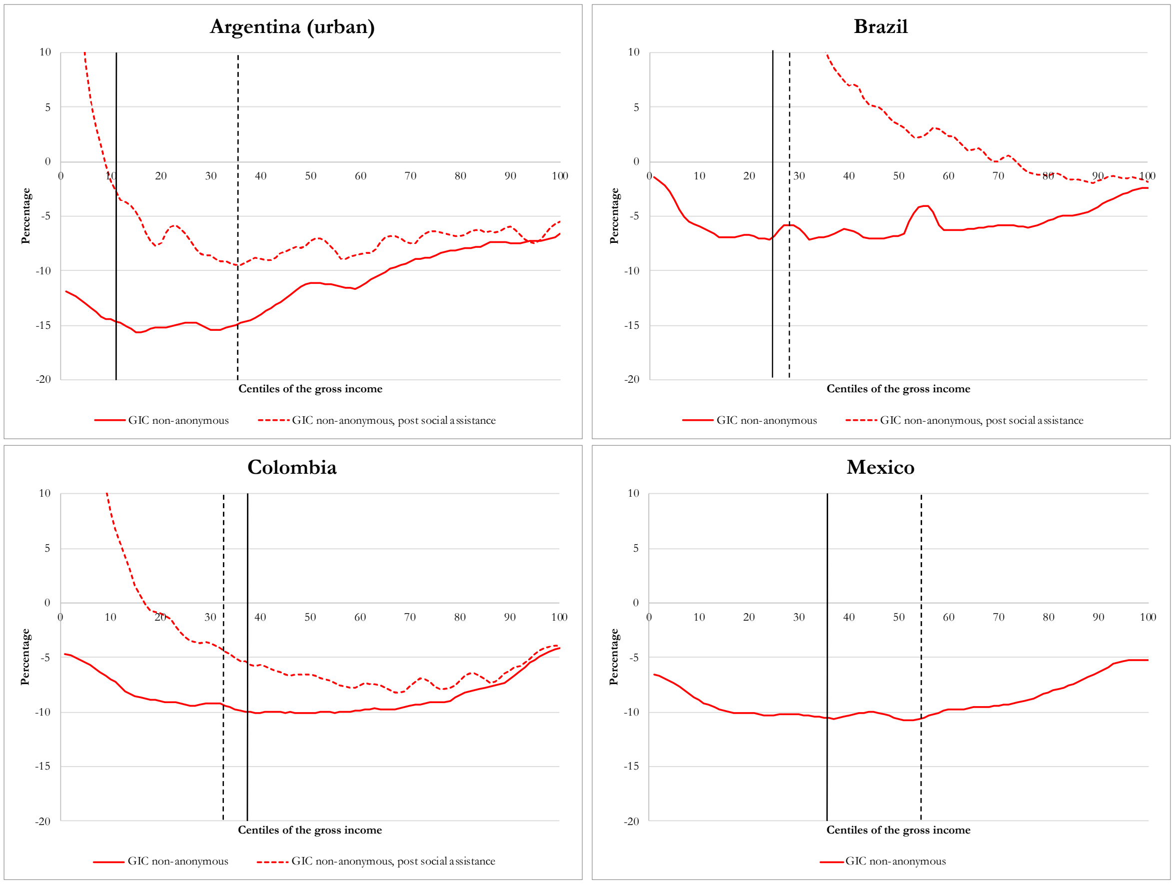
Notes: Poverty measured using the national poverty line.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

4. Distribution of Losses: Non-anonymous Growth Incidence Curves and Transition Matrices

The poverty and inequality comparisons above are anonymous. By (re-)ranking households from poorest to richest in each distribution, they do not consider the income trajectories of individual households. But those income trajectories are of considerable interest when income losses (or gains) differ, perhaps greatly, among households as they do here. To describe those trajectories, we use two non-anonymous distributional comparisons: non-anonymous growth incidence curves (GIC)—in this case, "contraction incidence curves"--.[41] In the appendix we also present results on mobility across broad income classes with income transition matrices whose results are summarized in Table 7 below. These income classes are: poor -- less than \$3.20 per day; moderate poor -- between \$3.20 and \$5.50 per day; lower-middle class -- between \$5.50 and \$11.50 per day; middle class -- between \$11.50 and \$57.60 per day; and rich -- more than \$57.60 per day.[42]

[41] Bourguignon (2011) discusses the theoretical and practical differences between the standard anonymous comparisons and non-anonymous methods, including the ones we use here.
[42] All cut-off values are in 2011 purchasing power parity (PPP) dollars. The default cut-off values \$3.20 and \$5.50 correspond to the income-category-specific poverty lines suggested in Jolliffe & Prydz (2016). The US\$3.20 and US\$5.50 PPP per day poverty lines are commonly used as extreme and moderate poverty lines for Latin America and roughly correspond to the median official extreme and moderate poverty lines in those countries. The \$11.50 and \$57.60 cutoffs correspond to cutoffs for the vulnerable and middle-class populations suggested for the 2005-era PPP conversion factors by López-Calva and Ortiz-Juarez (2014); \$11.50 and \$57.60 represent a United States CPI-inflation adjustment of the 2005-era \$10 and \$50 cutoffs. The US\$10 PPP per day line is the upper bound of those vulnerable to falling into poverty (and thus the lower bound of the middle class) in three Latin American countries, calculated by López-Calva and Ortiz-Juarez (2014). Ferreira and others (2013) find that an income of around US\$10 PPP also represents the income at which individuals in various Latin American countries tend to self-identify as belonging to the middle class and consider this a further justification for using it as the lower bound of the middle class. The US\$10 PPP per day line was also used as the lower bound of the middle class in Latin America in Birdsall (2010) and in developing countries in all regions of the world in Kharas (2010). The US\$50 PPP per day line is the upper bound of the middle class proposed by Ferreira and others (2013).

Figure 3. Non-anonymous Growth Incidence Curves



Notes: The dashed vertical line is the national poverty line and the bold vertical line is the $5.50 (moderate poor) per day international line (in 2011 PPP). Poverty lines based on the *ex ante* distribution of income.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Figure 3 shows the change in income at each percentile of the *ex ante* income distribution.[43] Households across the entire income distribution are worse off on average after the lockdowns, which is not surprising, but the losses tend to be higher for the middle deciles rather than the poorest, which perhaps is surprising. The latter reflects the fact that poorer households have a cushion given by the existing social assistance programs (the bottom area in Figure 1); it also reflects the fact that three types of income are both not at risk and concentrated at the top end of the *ex ante* income distribution: social security pensions, salaries earned in the public sector, and labor earnings of white collar workers who are CEO's, managers and researchers with internet access at home. The dotted lines show the GIC after considering the effect of the expanded social assistance. As expected, social assistance cuts the losses and, indeed, increases the income of poor households by significantly more in Brazil where the mitigation policies have

[43] In other words, each point on the curves shows the loss for the households that are, *ex ante*, in the shown centile in the x-axis. The y-axis shows the average change in per capita income. For example, the households in the first centile in Argentina could potentially lose about 13 percent of their pre-COVID per capita income before the expanded social assistance; that loss becomes a gain of roughly 30 percent once we consider expanded social assistance.

been much more ambitious compared to Argentina and Colombia.[44] In all three countries that have new or expanded social assistance transfers those transfers favor the *ex ante* poor.

Table 7 shows the downward mobility of the lower middle class and middle class caused by the crisis. Large shares of the *ex ante* poor fall into extreme poverty, and large shares of the *ex ante* lower-middle class fall into poverty. In the analyzed scenario, none of the previously middle class households fall into poverty as the losses to any individual household are smaller and thus not sufficient to drive a previously middle-class household into poverty. In Brazil and Argentina, the newly introduced social assistance seems to be sufficient to offset those losses and thus prevent households from falling into poverty.[45]

Table 7. Income Transitions

	Without Expanded Social Assistance			With Expanded Social Assistance		
Country	% of moderate poor who fall to poor	% of the vulnerable who fall to moderate poor or below	% of the middle class who fall to moderate poor or below	% of moderate poor who fall to poor	% of the vulnerable who fall to moderate poor or below	% of the middle class who fall to moderate poor or below
Argentina (urban)	27.4	24.5	0.0	10.6	15.3	0.0
Brazil	10.2	8.3	0.0	1.3	2.3	0.0
Colombia	17.1	15.3	0.0	12.5	12.8	0.0
Mexico	21.0	17.3	0.0			

Note: Income groups in terms of 2011 PPP are: poor: below $3.20; moderate poor: between $3.20 and below $5.50 per day; vulnerable: between $5.50 and below $11.50 per day; and middle class: between $11.50 and below $57.60 per day. For an explanation of the selection of these thresholds see section III.4.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

IV. Concluding Remarks

To contain the spread of the novel coronavirus, governments implemented lockdown policies of various degrees that, together with the global crisis, inevitably caused a sharp reduction in activity, a fall in employment and income, and a rise in poverty and inequality. Our microsimulations show that increases in poverty are worse than if we had assumed that each household's income declines by an equal proportion as many other studies of the crisis do. Contrary to prior expectations, we find that the worst effects are not on the poorest but those (roughly) in the middle of the *ex ante* income distribution. We also find that the expanded social assistance governments have introduced in response to the crisis have a large offsetting effect in Brazil, a significant effect in Argentina, and smaller in Colombia. The offsetting effect is nil in Mexico since no expansion of social assistance took place in the country. In Brazil, although the economic shock caused larger increases in poverty in the afrodescendant and indigenous

[44] Figure A1 in the appendix shows both the anonymous and non-anonymous GICs. The anonymous GIC tend to be upward sloping (except for the very poorest) and lie below the nonanonymous ones. In fact, the decline of incomes at the bottom before the expanded social assistance is much larger especially for the "concentrated scenario" because some of the households that were not among the poorest *ex ante* end up with almost zero income.
[45] The full set of income transition matrices can be found in Table A6 in the appendix.

populations than for others, the offsetting effects of expanded social assistance are larger for households whose head is afrodescendant or indigenous. In all countries the increase in poverty induced is similar for male- and female-headed households, but the offsetting effect of expanded social assistance is greater for female-headed households. This result, however, should not be extrapolated to the impact on women in general. In fact, available evidence suggests that unemployment, for instance, increased more for women than men.

Our analysis has relevant policy implications. First, implicit in our analysis is that a decisive fiscal response that counteracts the negative economic shock is crucial to mitigating the impact on living standards. As shown in Tables A7 and A8 in the appendix, higher overall contractions would have yielded significantly larger effects on inequality and poverty. Here Brazil and Mexico are on opposite ends with Brazil introducing one of the most ambitious counter-cyclical fiscal policy at the global level (especially for the developing world) while Mexico introducing one of the smallest fiscal rescue packages.[46] A second policy implication is that the existing cash transfer programs were able to provide an income floor for the poorest even in the absence of expanded social assistance. This speaks to the important of having such programs in place. Third, we learned that social assistance to workers in the informal sector can be introduced on a large scale and fast. Brazil stands out as having introduced a program (Auxilio Emergencial) that benefitted 67 million individuals within weeks. A large proportion of them was neither registered in the formal social security system or the administrative records of the noncontributory cash transfers. Yet, they were reached. On a considerably smaller scale, something analogous happened in Argentina and Colombia. Fourth, and as a consequence of these decisive expanded social assistance, the negative impact on the living standards of the poor and the vulnerable was contained in Argentina, Brazil and Colombia. In the case of Brazil, this containment was of such magnitude that inequality and poverty in 2020 appears to be lower than in 2019. In contrast, since there was no expanded social assistance in Mexico, the number of pandemic-induced new poor in this country is the highest of all four.

[46] See Lustig and Mariscal (2021) for a comparison between Brazil and Mexico.

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Appendix A

Table A1. Description of Existing and New Social Assistance Programs by Country

Argentina
NEW Ingreso Familiar de Emergencia is an unconditional transitory cash transfer to informal and vulnerable workers between 18 and 65 years old during the COVID-19 pandemic. The beneficiaries are individuals, and each household can receive only one allowance. Beneficiaries received three monthly payments of ARG $10,000 from May and July. The transfer amount represents 113.5% and 253.3% of the national and $5.5 PPP per day poverty lines. https://www.argentina.gob.ar/economia/medidas-economicas-COVID19/ingresofamiliardeemergencia
INCREASED Asignación Universal por Hijo is a conditional cash transfer program for children and adolescents (younger than 18 years old) living in poverty or vulnerability situations. The program includes conditions related to health and education obligations. The beneficiaries are individuals, and a household can receive up to 5 allowances. During the COVID-19 pandemic, the government announced a one-time extraordinary payment of ARG $3,100 in March. The transfer amount represents 35.2% and 78.5% of the national and $5.5 PPP per day poverty lines. https://www.anses.gob.ar/asignacion-universal-por-hijo https://www.argentina.gob.ar/economia/medidas-economicas-COVID19/bonos/AUH-AUE
Brazil
NEW Auxílio Emergencial is an unconditional transitory cash transfer to informal workers, individual microentrepreneurs, self-employed, and beneficiaries of Bolsa Família during the COVID-19 pandemic. The beneficiaries are individuals, and there are no restrictions on the number of allowances per household. Beneficiaries received five monthly payments of R $600 from April to August, and four monthly payments at half the original amount from September to December. The original transfer amount represents 121.9% and 140.3% of the national and $5.5 PPP per day poverty lines. https://www.caixa.gov.br/auxilio/PAGINAS/DEFAULT2.ASPX https://www.gov.br/cidadania/pt-br/servicos/sagi/relatorios/deolhonacidadania_3_2202.pdf
Colombia
NEW Ingreso Solidario is an unconditional transitory cash transfer program that aims to mitigate the situation of vulnerable households facing economic difficulties due to the COVID-19 pandemic. The beneficiaries of Ingreso Solidario are not obligated to any condition, but they must not be receiving any other social programs. The beneficiaries are households, and only one allowance per household is permitted. Beneficiarios received nine monthly payments of COL $160,000 from April to December. The program represents around 65.9% and 58.8% of the national and $5.5 PPP per day poverty lines. https://ingresosolidario.dnp.gov.co/

NEW Bogotá Solidaria is an unconditional cash transfer program (from Bogotá's Mayor Office) to support vulnerable and poor families in the city during the COVID-19 pandemic. The beneficiaries of Bogotá Solidario must not have any intra-household violence record. The beneficiaries are households, and only one allowance per household is permitted. Beneficiaries received five payments of COL $233,000. The program represents around 95.9% and 85.6% of the national and $5.5 PPP per day poverty lines. https://rentabasicabogota.gov.co/
INCREASED Familias en Acción is a conditional cash transfer program for children and adolescents (younger than 18 years old) living under food insecurity conditions. The beneficiaries are individuals, and a household can receive up to 3 allowances. The program includes conditions related to health and education obligations. During the COVID-19 pandemic, the government announced five extraordinary payments of COL $145,000 delivered every two months between March and December. The program represents around 59.7% and 53.2% of the national and $5.5 PPP per day poverty lines. https://prosperidadsocial.gov.co/sgpp/transferencias/familias-en-accion/ https://prosperidadsocial.gov.co/asi-vamos-contra-el-covid-19/
INCREASED Jóvenes en Acción is a conditional cash transfer program for young adults (between 16 to 24 years old) facing economic difficulties to continue or finish their studies. The program includes conditions related to eligibility criteria on other programs such as Familias en Accion and Red de la Superación de la Pobreza Extrema. The beneficiaries are individuals, and there are no restrictions on the number of allowances per household. During the COVID-19 pandemic, the government announced five-time extraordinary payments of COL $356,000 delivered every two months between March and December. The program represents around 146.5% and 130.7% of the national and $5.5 PPP per day poverty lines. https://prosperidadsocial.gov.co/sgpp/transferencias/jovenes-en-accion/ https://prosperidadsocial.gov.co/asi-vamos-contra-el-covid-19/
INCREASED Colombia Mayor is an unconditional cash transfer program for older adults without a pension or who live in extreme poverty or indigence. The beneficiaries are individuals, and there are no restrictions on the number of allowances per household. During the COVID-19 pandemic, the government announced five-time extraordinary payments of COL $160,000 delivered every two months between March and December. The program represents around 65.9% and 58.8% of the national and $5.5 PPP per day poverty lines. https://prosperidadsocial.gov.co/Noticias/disponible-pago-ordinario-y-extraordinario-para-beneficiarios-de-colombia-mayor/

Table A2. Employment by Sector

Panel (a) Argentina (urban)

Sector	Not at risk	At risk	Total
Agriculture	65,109	0	65,109
Mining	36,897	12,281	49,178
Manufacturing	736,190	663,709	1,399,899
Electricity, gas and water supply	52,041	37,702	89,743
Construction	119,479	984,050	1,103,529
Retail and wholesale	593,180	1,584,484	2,177,664
Accommodation and food service	112,358	344,128	456,486
Transport	150,331	490,213	640,544
Information and communication	86,118	170,555	256,673
Financial services	178,675	88,681	267,356
Real estate	36,809	30,604	67,413
Professional activities	695,307	251,581	946,888
Public administration	1,016,020	0	1,016,020
Education	1,012,903	0	1,012,903
Health	793,233	0	793,233
Other sectors	349,785	1,404,260	1,754,045
Total	6,034,435	6,062,248	12,096,683
%	49.9%	50.1%	

Panel (b) Brazil

Sector	Not at risk	At risk	Total
Agriculture	8,636,764	0	8,636,764
Mining	384,819	28,358	413,177
Manufacturing	3,996,924	6,910,053	10,906,977
Electricity, gas and water supply	744,746	153,773	898,519
Construction	321,999	6,493,117	6,815,116
Retail and wholesale	8,352,357	9,543,628	17,895,985
Accommodation and food service	385,260	5,236,263	5,621,523
Transport	2,641,323	2,194,322	4,835,645
Information and communication	1,241,353	102,909	1,344,262
Financial services	1,103,351	168,406	1,271,757
Real estate	70,257	476,066	546,323
Professional activities	4,062,780	3,481,562	7,544,342
Public administration	5,111,266	0	5,111,266
Education	6,588,520	0	6,588,520
Health	4,747,906	0	4,747,906
Other sectors	698,142	10,602,821	11,300,963
Total	49,087,767	45,391,278	94,479,045
%	52.0%	48.0%	

Panel (c) Colombia

Sector	Not at risk	At risk	Total
Agriculture	3,515,167	0	3,515,167
Mining	195,612	1,222	196,834
Manufacturing	1,450,032	1,089,303	2,539,335
Electricity, gas and water supply	113,037	38,081	151,118
Construction	120,927	1,392,706	1,513,633
Retail and wholesale	1,632,476	2,815,331	4,447,807
Accommodation and food service	26,771	1,492,637	1,519,408
Transport	518,790	946,252	1,465,042
Information and communication	213,505	46,873	260,378
Financial services	305,304	26,567	331,871
Real estate	40,836	311,224	352,060
Professional activities	792,673	554,786	1,347,459
Public administration	711,302	0	711,302
Education	959,010	0	959,010
Health	956,935	0	956,935
Other sectors	205,906	1,688,689	1,894,595
Total	11,758,283	10,403,671	22,161,954
%	53.1%	46.9%	

Panel (d) Mexico

Sector	Not at risk	At risk	Total
Agriculture	8,953,313	0	8,953,313
Mining	198,514	0	198,514
Manufacturing	4,098,366	5,470,030	9,568,396
Electricity, gas and water supply	220,675	655	221,330
Construction	348,183	4,477,639	4,825,822
Retail and wholesale	5,893,101	5,145,482	11,038,583
Accommodation and food service	181,228	4,754,290	4,935,518
Transport	813,780	1,628,415	2,442,195
Information and communication	470,479	0	470,479
Financial services	558,741	557	559,298
Real estate	377,231	108	377,339
Professional activities	1,351,674	31,126	1,382,800
Public administration	2,172,350	0	2,172,350
Education	2,818,952	0	2,818,952
Health	1,670,654	0	1,670,654
Other sectors	6,208,673	5,566,657	11,775,330
Total	36,335,914	27,074,959	63,410,873
%	57.3%	42.7%	

Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A3. Gini Coefficient for Scenarios with Losses Similar to the Loss Projections by IMF (2021)

			Without Expanded Social Assistance		With Expanded Social Assistance	
Country	Scenario	Gini Coefficient *Ex ante*	Gini Coefficient *Ex post*	Change (Gini points)	Gini Coefficient *Ex post* + Social Assistance	Change (Gini points)
Argentina (urban)	40% lose 90%	44.4	48.6	4.2	46.9	2.5
Argentina (urban)	50% lose 70%	44.4	47.7	3.3	46.0	1.6
Argentina (urban)	60% lose 60%	44.4	47.5	3.0	45.7	1.3
Argentina (urban)	70% lose 50%	44.4	47.0	2.6	45.3	0.9
Argentina (urban)	90% lose 40%	44.4	46.7	2.2	45.1	0.7
Brazil	20% lose 80%	55.4	57.0	1.6	53.3	-2.1
Brazil	30% lose 50%	55.4	56.4	1.1	52.7	-2.6
Brazil	40% lose 40%	55.4	56.4	1.0	52.7	-2.7
Brazil	50% lose 30%	55.4	56.2	0.8	52.5	-2.8
Brazil	80% lose 20%	55.4	56.1	0.8	52.5	-2.9
Colombia	20% lose 100%	55.0	58.2	3.1	56.9	1.9
Colombia	30% lose 70%	55.0	57.2	2.2	56.0	1.0
Colombia	40% lose 50%	55.0	56.6	1.6	55.5	0.4
Colombia	50% lose 40%	55.0	56.4	1.4	55.2	0.2
Colombia	70% lose 30%	55.0	56.2	1.2	55.1	0.1
Colombia	100% lose 20%	55.0	56.0	0.9	54.8	-0.2
Mexico	30% lose 80%	46.4	49.3	2.9		
Mexico	40% lose 60%	46.4	48.6	2.2		
Mexico	50% lose 50%	46.4	48.3	1.9		
Mexico	60% lose 40%	46.4	47.9	1.5		
Mexico	80% lose 30%	46.4	47.7	1.3		

Notes: Change is the difference between *ex post* and *ex ante* Gini coefficients.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A4. Incidence of Poverty for with Losses Similar to the Loss Projections by IMF (2021)

Country	Scenario	Headcount ratio *Ex ante* (%)	Without Expanded Social Assistance: Headcount ratio *Ex post* (%)	Without Expanded Social Assistance: Change (pp.)	Without Expanded Social Assistance: New poor (in millions)	With Expanded Social Assistance: Headcount ratio *Ex post* + Social Assistance (%)	With Expanded Social Assistance: Change (pp.)	With Expanded Social Assistance: New poor (in millions)
			Panel (a) National Poverty Line					
Argentina (urban)	40% lose 90%	35.5	42.8	7.2	2.0	40.3	4.8	1.4
Argentina (urban)	50% lose 70%	35.5	42.9	7.4	2.1	40.3	4.7	1.3
Argentina (urban)	60% lose 60%	35.5	43.1	7.6	2.1	40.6	5.1	1.4
Argentina (urban)	70% lose 50%	35.5	43.0	7.4	2.1	40.7	5.2	1.5
Argentina (urban)	90% lose 40%	35.5	43.1	7.6	2.1	40.7	5.1	1.4
Brazil	20% lose 80%	28.2	31.8	3.6	7.5	26.1	-2.0	-4.3
Brazil	30% lose 50%	28.2	31.0	2.8	5.8	25.2	-3.0	-6.2
Brazil	40% lose 40%	28.2	31.1	3.0	6.2	25.1	-3.0	-6.3
Brazil	50% lose 30%	28.2	30.9	2.7	5.6	24.8	-3.3	-6.9
Brazil	80% lose 20%	28.2	31.0	2.9	6.0	24.9	-3.3	-6.8
Colombia	20% lose 100%	31.8	36.9	5.2	2.5	34.8	3.0	1.5
Colombia	30% lose 70%	31.8	37.1	5.3	2.6	35.0	3.2	1.6
Colombia	40% lose 50%	31.8	36.5	4.7	2.3	34.4	2.6	1.3
Colombia	50% lose 40%	31.8	36.5	4.7	2.3	34.2	2.4	1.2
Colombia	70% lose 30%	31.8	36.4	4.6	2.3	34.1	2.3	1.1
Colombia	100% lose 20%	31.8	36.0	4.2	2.1	33.4	1.7	0.8
Mexico	30% lose 80%	53.8	58.6	4.9	6.1			
Mexico	40% lose 60%	53.8	59.0	5.2	6.5			
Mexico	50% lose 50%	53.8	59.5	5.7	7.1			
Mexico	60% lose 40%	53.8	59.3	5.5	6.9			
Mexico	80% lose 30%	53.8	59.3	5.5	6.9			
			Panel (b) $5.5 PPP Poverty Line					
Argentina (urban)	40% lose 90%	10.9	19.1	8.2	2.3	16.8	5.9	1.7
Argentina (urban)	50% lose 70%	10.9	18.0	7.1	2.0	14.9	4.0	1.1
Argentina (urban)	60% lose 60%	10.9	17.5	6.6	1.9	13.9	3.0	0.9
Argentina (urban)	70% lose 50%	10.9	16.5	5.6	1.6	13.0	2.1	0.6
Argentina (urban)	90% lose 40%	10.9	15.8	4.9	1.4	12.8	1.9	0.5
Brazil	20% lose 80%	25.4	28.9	3.5	7.4	22.2	-3.2	-6.7
Brazil	30% lose 50%	25.4	27.9	2.6	5.4	21.0	-4.4	-9.1
Brazil	40% lose 40%	25.4	27.9	2.5	5.3	21.0	-4.4	-9.2
Brazil	50% lose 30%	25.4	27.5	2.1	4.5	20.6	-4.7	-9.9
Brazil	80% lose 20%	25.4	27.6	2.2	4.6	20.6	-4.7	-9.9
Colombia	20% lose 100%	37.6	42.6	5.0	2.5	40.8	3.2	1.6
Colombia	30% lose 70%	37.6	42.7	5.2	2.5	41.1	3.5	1.7
Colombia	40% lose 50%	37.6	42.3	4.8	2.3	40.6	3.0	1.5
Colombia	50% lose 40%	37.6	42.2	4.7	2.3	40.4	2.9	1.4
Colombia	70% lose 30%	37.6	42.1	4.5	2.2	40.3	2.7	1.3
Colombia	100% lose 20%	37.6	41.8	4.2	2.1	39.8	2.2	1.1
Mexico	30% lose 80%	34.9	41.6	6.8	8.5			
Mexico	40% lose 60%	34.9	41.8	6.9	8.7			
Mexico	50% lose 50%	34.9	42.1	7.3	9.1			
Mexico	60% lose 40%	34.9	41.6	6.7	8.4			
Mexico	80% lose 30%	34.9	41.3	6.5	8.1			

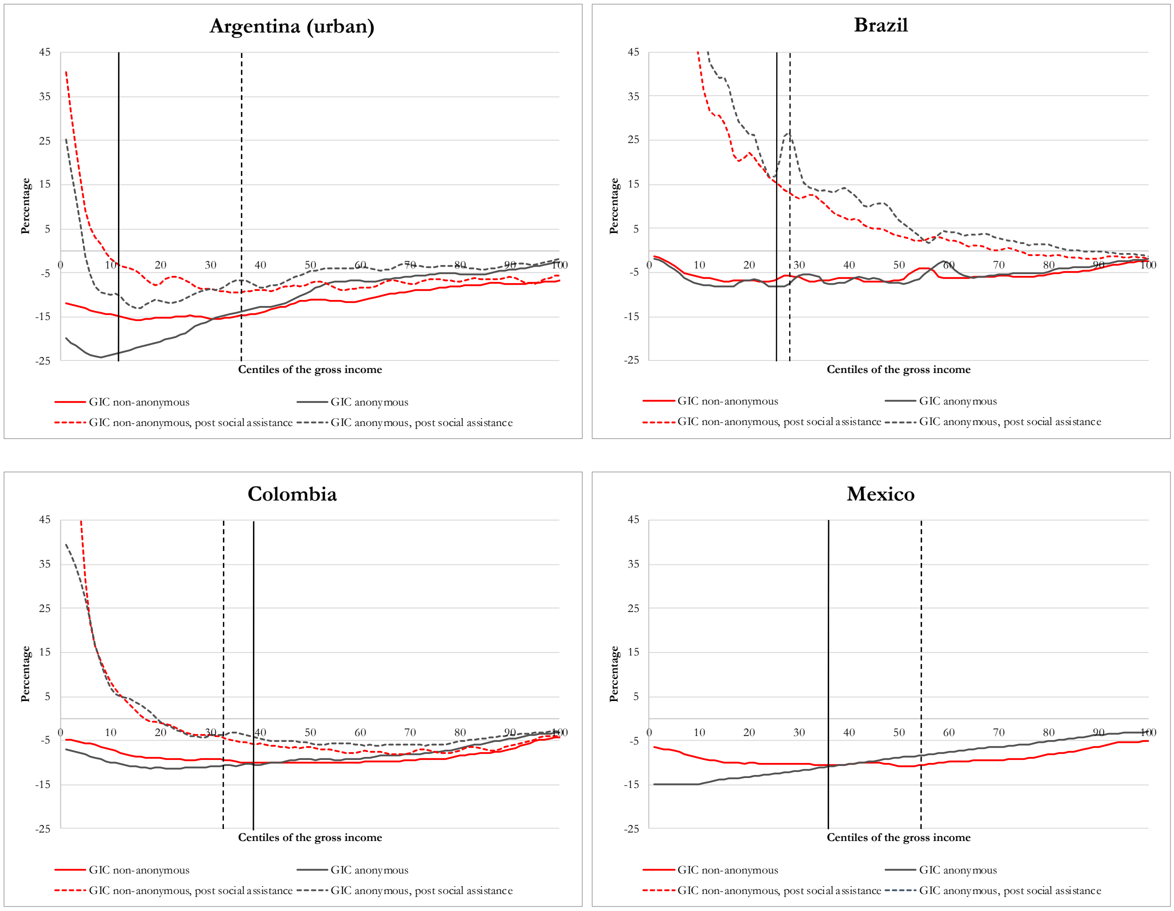
Notes: Change is the difference between *ex post* and *ex ante* headcount ratios. The number of new poor is calculated as the change in *ex post* and *ex ante* headcount ratios times the projected population for 2020 obtained from the World Bank World Development Indicators. pp: percentage points.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A5. Squared Poverty Gap

Country	Squared poverty gap *Ex ante* (%)	Without Expanded Social Assistance: Squared poverty gap *Ex post* (%)	Without Expanded Social Assistance: Change (pp.)	With Expanded Social Assistance: Squared poverty gap *Ex post* + Social Assistance (%)	With Expanded Social Assistance: Change (pp.)
Panel (a) National Poverty Line					
Argentina (urban)	7.8	11.1	3.3	9.0	1.2
Brazil	9.0	9.7	0.7	5.1	-3.8
Colombia	8.9	10.3	1.3	8.7	-0.2
Mexico	10.7	13.6	2.9		
Panel (b) $5.5 PPP Poverty Line					
Argentina (urban)	2.2	3.2	1.0	1.8	-0.3
Brazil	7.7	8.3	0.6	4.0	-3.7
Colombia	11.1	12.6	1.5	11.0	-0.1
Mexico	6.0	7.9	1.9		

Note: Change is the difference between *ex post* and *ex ante* squared poverty gaps. pp: percentage points.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Figure A1. Anonymous and Non-anonymous Growth Incidence Curves



Notes: The dashed vertical line is the national poverty line and the bold vertical line is the $5.50 (moderate poor) per day international line (in 2011 PPP). Poverty lines based on the *ex ante* distribution of income. Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A6. Transition Matrices

Panel (a) Argentina (urban)

Income group		Post: Poor y < 3.20	Moderate poor 3.20 <= y < 5.50	Vulnerable 5.50 <= y < 11.50	Middle Class 11.50 <= y < 57.60	Rich 57.60 <= y	% Population
Pre	y < 3.20	80.8%	19.2%	0.0%	0.0%	0.0%	100.0%
	3.20 <= y < 5.50	10.6%	69.1%	20.3%	0.0%	0.0%	100.0%
	5.50 <= y < 11.50	0.0%	15.3%	78.4%	6.2%	0.0%	100.0%
	11.50 <= y < 57.60	0.0%	0.0%	9.8%	90.0%	0.2%	100.0%
	57.60 <= y	0.0%	0.0%	0.0%	14.4%	85.6%	100.0%
Change wrt. the same group		-0.2%	29.5%	11.0%	-6.3%	-12.5%	

Panel (b) Brazil

Income group		Post: Poor y < 3.20	Moderate poor 3.20 <= y < 5.50	Vulnerable 5.50 <= y < 11.50	Middle Class 11.50 <= y < 57.60	Rich 57.60 <= y	% Population
Pre	y < 3.20	58.9%	38.0%	3.1%	0.0%	0.0%	100.0%
	3.20 <= y < 5.50	1.3%	57.9%	40.6%	0.2%	0.0%	100.0%
	5.50 <= y < 11.50	0.0%	2.3%	87.5%	10.2%	0.0%	100.0%
	11.50 <= y < 57.60	0.0%	0.0%	3.2%	96.7%	0.2%	100.0%
	57.60 <= y	0.0%	0.0%	0.0%	3.6%	96.4%	100.0%
Change wrt. the same group		-39.9%	5.1%	12.6%	3.4%	-2.2%	

Panel (c) Colombia

Income group		Post: Poor y < 3.20	Moderate poor 3.20 <= y < 5.50	Vulnerable 5.50 <= y < 11.50	Middle Class 11.50 <= y < 57.60	Rich 57.60 <= y	% Population
Pre	y < 3.20	93.1%	6.8%	0.1%	0.0%	0.0%	100.0%
	3.20 <= y < 5.50	12.5%	81.3%	6.2%	0.0%	0.0%	100.0%
	5.50 <= y < 11.50	0.0%	12.8%	85.9%	1.3%	0.0%	100.0%
	11.50 <= y < 57.60	0.0%	0.0%	11.5%	88.5%	0.0%	100.0%
	57.60 <= y	0.0%	0.0%	0.0%	6.8%	93.2%	100.0%
Change wrt. the same group		4.0%	10.9%	1.3%	-9.6%	-6.8%	

Panel (d) Mexico

Income group		Post: Poor y < 3.20	Moderate poor 3.20 <= y < 5.50	Vulnerable 5.50 <= y < 11.50	Middle Class 11.50 <= y < 57.60	Rich 57.60 <= y	% Population
Pre	y < 3.20	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	3.20 <= y < 5.50	21.0%	79.0%	0.0%	0.0%	0.0%	100.0%
	5.50 <= y < 11.50	0.0%	17.3%	82.7%	0.0%	0.0%	100.0%
	11.50 <= y < 57.60	0.0%	0.0%	12.6%	87.4%	0.0%	100.0%
	57.60 <= y	0.0%	0.0%	0.0%	9.1%	90.9%	100.0%
Change wrt. the same group		36.8%	8.6%	-8.7%	-12.2%	-9.1%	

Note: Income groups in terms of 2011 PPP. Post income groups based on the *ex post* with expanded social assistance distribution of income.
Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A7. Gini Coefficient for All Possible Scenarios

Panel (a) Argentina (urban)

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	44.4	44.4	44.4	44.4	44.4	44.4	44.4	44.4	44.4	44.4
10%	44.5	44.5	44.6	44.7	44.8	44.9	45.1	45.3	45.5	45.7
20%	44.5	44.6	44.8	45.0	45.2	45.4	45.7	46.1	46.5	47.0
30%	44.5	44.7	44.9	45.2	45.5	45.9	46.4	46.9	47.5	48.3
40%	44.6	44.8	45.1	45.5	45.9	46.4	47.0	47.8	48.6	49.5
50%	44.7	44.9	45.3	45.8	46.3	46.9	47.7	48.6	49.7	50.9
60%	44.7	45.1	45.5	46.0	46.7	47.5	48.4	49.4	50.7	52.2
70%	44.7	45.1	45.6	46.3	47.0	47.9	48.9	50.2	51.7	53.5
80%	44.8	45.2	45.8	46.4	47.2	48.2	49.4	50.8	52.5	54.6
90%	44.8	45.3	45.9	46.7	47.6	48.6	50.0	51.6	53.5	55.9
100%	44.9	45.4	46.1	46.9	47.9	49.2	50.6	52.4	54.6	57.2

Panel (b) Brazil

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	55.4	55.4	55.4	55.4	55.4	55.4	55.4	55.4	55.4	55.4
10%	55.4	55.5	55.5	55.6	55.7	55.9	56.0	56.2	56.4	56.6
20%	55.5	55.6	55.7	55.9	56.1	56.3	56.6	57.0	57.4	57.9
30%	55.5	55.7	55.9	56.1	56.4	56.8	57.2	57.7	58.4	59.1
40%	55.5	55.8	56.0	56.4	56.8	57.2	57.8	58.5	59.3	60.3
50%	55.6	55.9	56.2	56.6	57.1	57.7	58.4	59.2	60.2	61.5
60%	55.6	56.0	56.4	56.8	57.4	58.1	59.0	60.0	61.2	62.7
70%	55.7	56.1	56.5	57.1	57.8	58.6	59.6	60.7	62.2	63.9
80%	55.7	56.1	56.7	57.3	58.1	59.0	60.1	61.4	63.1	65.1
90%	55.8	56.2	56.8	57.5	58.4	59.4	60.7	62.2	64.0	66.4
100%	55.8	56.3	57.0	57.7	58.7	59.8	61.2	62.9	64.9	67.6

Panel (c) Colombia

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0
10%	55.1	55.1	55.2	55.3	55.4	55.6	55.7	56.0	56.2	56.5
20%	55.1	55.2	55.4	55.6	55.9	56.2	56.6	57.0	57.5	58.2
30%	55.2	55.3	55.6	55.9	56.2	56.7	57.2	57.8	58.6	59.6
40%	55.2	55.5	55.8	56.2	56.6	57.2	57.9	58.8	59.8	61.1
50%	55.2	55.6	55.9	56.4	57.0	57.7	58.6	59.7	61.0	62.6
60%	55.3	55.6	56.1	56.6	57.3	58.2	59.2	60.5	62.1	64.1
70%	55.3	55.7	56.2	56.9	57.6	58.6	59.8	61.3	63.2	65.5
80%	55.4	55.8	56.4	57.1	58.0	59.0	60.4	62.1	64.2	67.0
90%	55.4	55.9	56.5	57.3	58.3	59.5	61.0	62.9	65.3	68.4
100%	55.4	56.0	56.6	57.5	58.5	59.8	61.4	63.5	66.2	69.8

Panel (d) Mexico

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	46.4	46.4	46.4	46.4	46.4	46.4	46.4	46.4	46.4	46.4
10%	46.4	46.5	46.6	46.7	46.8	47.0	47.1	47.4	47.6	47.9
20%	46.5	46.6	46.8	47.0	47.2	47.5	47.9	48.3	48.8	49.5
30%	46.5	46.7	46.9	47.2	47.6	48.0	48.6	49.3	50.1	51.0
40%	46.6	46.8	47.1	47.5	48.0	48.6	49.3	50.2	51.2	52.5
50%	46.6	46.9	47.2	47.7	48.3	49.0	49.9	51.0	52.4	54.0
60%	46.6	47.0	47.4	47.9	48.6	49.5	50.5	51.8	53.4	55.4
70%	46.7	47.1	47.5	48.2	49.0	50.0	51.2	52.7	54.6	56.9
80%	46.7	47.1	47.7	48.4	49.3	50.4	51.8	53.5	55.6	58.4
90%	46.8	47.2	47.8	48.6	49.6	50.8	52.4	54.3	56.7	59.8
100%	46.8	47.3	47.9	48.8	49.8	51.1	52.8	54.9	57.6	61.1

Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Table A8. Incidence of Poverty for All Possible Scenarios; $5.5 PPP Poverty Line

Panel (a) Argentina (urban)

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%
10%	11.0%	11.2%	11.3%	11.5%	11.8%	12.0%	12.4%	12.7%	13.0%	13.3%
20%	11.0%	11.4%	11.7%	12.1%	12.6%	13.1%	13.8%	14.5%	15.1%	15.6%
30%	11.1%	11.5%	12.0%	12.5%	13.2%	14.1%	15.0%	16.2%	17.0%	17.7%
40%	11.1%	11.8%	12.4%	13.1%	14.1%	15.3%	16.6%	18.0%	19.1%	20.0%
50%	11.2%	12.0%	12.7%	13.7%	14.8%	16.4%	18.0%	19.8%	21.2%	22.4%
60%	11.3%	12.3%	13.2%	14.3%	15.7%	17.5%	19.5%	21.7%	23.3%	24.7%
70%	11.4%	12.5%	13.5%	14.8%	16.5%	18.6%	21.0%	23.6%	25.5%	27.2%
80%	11.5%	12.7%	13.8%	15.3%	17.3%	19.7%	22.4%	25.4%	27.5%	29.5%
90%	11.6%	12.8%	14.1%	15.8%	18.0%	20.8%	23.9%	27.3%	29.7%	31.9%
100%	11.6%	13.1%	14.5%	16.4%	18.8%	21.9%	25.4%	29.3%	31.9%	34.4%

Panel (b) Brazil

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	25.4%	25.4%	25.4%	25.4%	25.4%	25.4%	25.4%	25.4%	25.4%	25.4%
10%	25.5%	25.7%	25.8%	26.0%	26.3%	26.5%	26.9%	27.2%	27.4%	27.6%
20%	25.5%	25.9%	26.2%	26.6%	27.1%	27.6%	28.3%	28.9%	29.4%	29.7%
30%	25.6%	26.1%	26.6%	27.2%	27.9%	28.8%	29.7%	30.7%	31.4%	31.9%
40%	25.7%	26.4%	27.1%	27.9%	28.8%	29.9%	31.1%	32.4%	33.4%	34.1%
50%	25.8%	26.7%	27.5%	28.5%	29.7%	31.0%	32.5%	34.1%	35.3%	36.2%
60%	26.0%	27.0%	27.9%	29.1%	30.5%	32.1%	34.0%	35.9%	37.4%	38.4%
70%	26.1%	27.3%	28.5%	29.8%	31.5%	33.4%	35.5%	37.7%	39.4%	40.6%
80%	26.2%	27.6%	28.9%	30.5%	32.3%	34.5%	36.9%	39.5%	41.4%	42.8%
90%	26.3%	27.8%	29.4%	31.1%	33.2%	35.7%	38.4%	41.3%	43.5%	45.1%
100%	26.4%	28.1%	29.8%	31.8%	34.1%	36.9%	39.9%	43.1%	45.5%	47.3%

Panel (c) Colombia

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	37.6%	37.6%	37.6%	37.6%	37.6%	37.6%	37.6%	37.6%	37.6%	37.6%
10%	37.8%	38.1%	38.4%	38.6%	38.8%	39.1%	39.4%	39.7%	39.8%	40.0%
20%	38.0%	38.5%	39.0%	39.4%	40.0%	40.6%	41.2%	41.7%	42.2%	42.6%
30%	38.2%	38.8%	39.5%	40.2%	41.0%	41.9%	42.7%	43.6%	44.3%	44.9%
40%	38.4%	39.3%	40.3%	41.2%	42.3%	43.5%	44.6%	45.8%	46.6%	47.5%
50%	38.7%	39.7%	40.9%	42.2%	43.7%	45.1%	46.3%	47.7%	48.8%	49.9%
60%	38.9%	40.1%	41.6%	43.2%	44.8%	46.5%	48.1%	49.7%	51.1%	52.2%
70%	39.0%	40.5%	42.1%	44.0%	45.9%	47.9%	49.7%	51.7%	53.3%	54.5%
80%	39.2%	40.8%	42.6%	44.8%	47.0%	49.3%	51.4%	53.7%	55.5%	56.9%
90%	39.3%	41.2%	43.3%	45.7%	48.3%	50.7%	53.1%	55.8%	57.8%	59.4%
100%	39.6%	41.8%	44.1%	46.7%	49.6%	52.5%	55.2%	58.1%	60.3%	62.1%

Panel (d) Mexico

% of income lost / % losing income	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	34.9%	34.9%	34.9%	34.9%	34.9%	34.9%	34.9%	34.9%	34.9%	34.9%
10%	35.1%	35.3%	35.6%	35.9%	36.3%	36.6%	36.8%	37.0%	37.2%	37.4%
20%	35.3%	35.8%	36.4%	37.0%	37.7%	38.3%	38.9%	39.3%	39.7%	40.1%
30%	35.6%	36.3%	37.2%	38.1%	39.2%	40.1%	41.0%	41.6%	42.2%	42.7%
40%	35.9%	36.9%	38.0%	39.3%	40.7%	41.8%	42.9%	43.9%	44.6%	45.3%
50%	36.1%	37.4%	38.9%	40.5%	42.1%	43.6%	44.9%	46.1%	47.1%	47.9%
60%	36.3%	37.9%	39.7%	41.6%	43.5%	45.3%	46.9%	48.3%	49.5%	50.5%
70%	36.6%	38.5%	40.6%	42.8%	45.0%	47.1%	49.0%	50.7%	52.0%	53.2%
80%	36.8%	38.9%	41.3%	43.9%	46.4%	48.8%	51.0%	52.9%	54.4%	55.8%
90%	37.1%	39.4%	42.1%	44.9%	47.8%	50.6%	53.0%	55.2%	56.9%	58.5%
100%	37.3%	40.0%	42.9%	46.1%	49.4%	52.5%	55.2%	57.6%	59.5%	61.3%

Source: Authors' calculations based on ENIGH (2018), EPH (2019), GEIH (2019), PNADC (2019).

Appendix B

The Online Appendix B can be found online at https://commitmentoequity.org/wp-content/uploads/2021/06/Appendix-B-of-The-Impact-of-COVID-19-and-Expanded-Social-Assistance-on-Inequality-Poverty-and-Mobility-in-Argentina-Brazil-Colombia-and-Mexico.pdf.