THE IMPACT OF COVID-19 ON INEQUALITY AND POVERTY IN MEXICO

EL IMPACTO DEL COVID-19 EN LA DESIGUALDAD Y LA POBREZA EN MÉXICO

Nora Lustig

Valentina Martínez Pabón

Tulane University

Resumen: El impacto distributivo del COVID-19 en el corto plazo se estima mediante microsimulaciones. Si bien el incremento potencial de la pobreza es significativo, cuando se compara con el ingreso pre-shock los grupos que más pierden son los pobres y los vulnerables a la pobreza. El impacto sobre la pobreza es más severo para hogares urbanos. La pobreza sube relativamente menos para los hogares rurales y la población indígena. México sobresale porque -comparado con Argentina, Brasil y Colombia- el gobierno no puso en marcha programas de transferencias adicionales para mitigar el impacto de la pandemia sobre los niveles de vida.

Abstract: We use microsimulation to estimate the short-term distributional consequences of the COVID-19 pandemic in Mexico. Although the potential increase in poverty is significant, we find that compared to their pre-shock income, those who lost the most are the moderate poor and the vulnerable to poverty. We find that the impact on poverty is more severe for urban households. Poverty increases less for rural households and the indigenous population. Compared to Argentina, Brazil, and Colombia, Mexico stands out because the government did not introduce additional transfers to mitigate the impact of the pandemic on living standards.

Clasificación JEL/JEL Classification: C63, D31, I32, I38

Palabras clave/keywords: COVID-19; inequality; Mexico; poverty; microsimulations

Fecha de recepción: 11 VIII 2020   Fecha de aceptación: 14 I 2021

1. Introduction

The recent COVID-19 pandemic has come at overwhelming health and economic costs to Latin America, Mexico in particular.[1] In August 2020, Mexico was among the top ten countries in terms of infections and the top five in terms of deaths per one-hundred thousand inhabitants.[2] To contain the spread of the virus, governments implemented lockdown policies of various degrees.[3] Although in Mexico, the federal government did not implement full-lockdown measures, "stay-at-home" recommendations were put in place. Inevitably, these measures caused a sharp reduction of activity, a fall in employment and income, and a rise in poverty and inequality.[4] In this paper, we analyze the impact of the economic dislocation on poverty, inequality, and income mobility in Mexico, and compare it with the impacts in the three other largest Latin American countries: Argentina, Brazil, and Colombia.[5] In addition to lockdowns to control infection rates, governments in these three countries have introduced new or expanded social assistance measures to varying degrees. In Mexico, there has been no such expansion.

Based on the economic sector in which household members work, we use microsimulation to estimate potential income losses at the household level, using the National Survey of Household Income and Expenditure (*Encuesta Nacional de Ingresos y Gastos de los Hogares*, ENIGH, 2018).[6] The simulations first identify individuals whose

[1] IMF (2020).

[2] See https://coronavirus.jhu.edu/data/mortality.

[3] For a description of lockdowns by country see, for example, Pages *et al.* (2020).

[4] According to IMF (2020) and ECLAC (2020), the region's GDP could contract in 2020 by 9.4 and 9.1 percent, respectively.

[5] Note that mobility here refers to *ex-ante/ex-post* comparisons and not to mobility over time or intergenerational mobility.

[6] Our exercise falls under the definition of microsimulation by the International Microsimulation Association. Namely: The International Microsimulation Association defines microsimulation as a modeling technique that operates at the level of individual units such as persons, households, vehicles, or firms. Within the model each unit is represented by a record containing a unique identifier and a set of associated attributes, for example, a list of persons with known age, sex, marital and employment status; or a list of vehicles with known origins, destinations, and operational characteristics. A set of rules (transition probabilities) are then applied to these units leading to simulated changes in state and behavior.

income is "at risk" because they work in sectors in which COVID-19 has reduced or eliminated activity. We base our determination of at-risk income on the economic sectors in which one works. We assume that income derived from work in sectors that are "essential" is not at risk, while any income earned in "nonessential" sectors is at risk. For Mexico, we use the International Labour Organization (ILO) definition of essential sectors. 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 one-hundred possible outcomes. To narrow our focus to reasonable possibilities, we choose a combination of the two key parameters that yields a decline in *per capita* income that comes closest to the International Monetary Fund (IMF) World Economic Outlook forecast from October 2020: 9.0 percent for Mexico.[7] Even here, there are multiple possibilities of which we present two extremes, one in which a smaller proportion of households lose a large share of their income and another in which a larger number of households lose less income. To complete the analysis, we construct a simulated income distribution that incorporates the losses we estimate and compare it with the *ex-ante* distribution. 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.[8]

This paper makes several contributions. First, most existing ex-

These rules may be deterministic (probability = 1), such as changes in tax liability resulting from changes in tax regulations, or stochastic (probability <=1), such as chance of dying, marrying, giving birth or moving within a given time period. In either case, the result is an estimate of the outcomes of applying these rules, possibly over many time steps, including both total overall aggregate change and (importantly) the way this change is distributed in the population or location that is being modeled. For an overview of microsimulation models for distributional analysis and impact assessment of policy reforms see Figari *et al.* (2015).

[7] We use the IMF predictions for 2020 adjusted to *per capita* growth rates using data on population growth for the latest year available. Then, following the method suggested by Ravallion (2003) and applied by Lakner *et al.* (2020), we assume a "pass-through" of GDP growth to household (gross) income growth of 0.85.

[8] This is analogous to the non-anonymous growth incidence curves in Bourguignon (2011), albeit here describing a contraction.

ercises that predict the impact of COVID-19 on poverty assume that income losses are proportional across the income distribution.[9] Two exceptions are the Economic Commission for Latin America and the Caribbean (ECLAC, 2020) and Hufmann and Najera (2020), who combine data from several surveys -including post-COVID telephonic surveys and use small-sample and matching methods to predict post-COVID incomes and extreme poverty. Based on existing information, however, the distribution of income is changing -and changing fast- during the pandemic.[10] Our use of microsimulation allows us to relax the equal loss assumption and so 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. Second, we carry out the analysis not only at the national level but also by ethnicity and gender of the household head, and by urban and rural areas. Third, we test the sensitivity of our results to two assumptions: the definition of income "at risk" and the size of the aggregate contraction.

Our findings show that the potential impact of the economic dislocation on inequality and poverty can be quite large. The Gini coefficient could rise between 1.3 and 3.7 points. The increase in the number of poor (measured with the national poverty line) could be between 7.5 and 8.7 million. In contrast, a distribution-neutral simulation would result in an increase of 6.8 million individuals. In addition, contrary to many people's priors, the non-anonymous growth incidence curves show that income losses could be greater in the middle deciles of the *ex-ante* distribution. That is, losses are more pronounced for the moderate poor and those vulnerable to falling below the poverty line rather than among the poorest. This is so because social assistance programs and consumption of own production represent a larger share of total gross income for the poorest; essentially, these two items put a "floor" for their incomes. The economic dislocation is likely to cause a smaller increase in poverty for rural areas because it is here where consumption of own production -as a share of gross income- is the largest. Because the indigenous population is concentrated in rural areas, the rise in poverty among the indigenous population is potentially lower than for the non-indigenous one. The expected rise in poverty is similar for male and female-headed households.

[9] CONEVAL (2020), Gerszon *et al.* (2020), and World Bank (2020).

[10] See, for example, Bottan *et al.* (2020), Brussevich *et al.* (2020), Busso *et al.* (2020), INEGI (2020), Universidad Iberoamericana (2020).

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. The depth and duration of the crisis are still uncertain, and the Mexican economy could end up contracting by more (or less) than the IMF's October 2020 projections. Our results depend on the specific assumptions we make about income sources that are "at risk" and the extent to which losses are concentrated or dispersed across households. Finally, our exercise does not include social assistance measures undertaken by the Mexican states (or other subnational entities).[11]

2. Data and methodology

For our simulations, we use the ENIGH 2018, the most recent income expenditure survey available for Mexico. We use gross income *per capita* as the welfare indicator. Gross income is defined as labor income plus rents, private transfers, pensions, consumption of own production, the rental value of owner-occupied housing and government cash transfers before any direct taxes. We update gross incomes for Mexico to 2019 by the rate of growth of the Gross Domestic Product (GDP) *per capita* for 2019 multiplied by a so-called pass through of 0.85.[12] Also, for Mexico, we update gross incomes to take into account the significant reforms introduced to the cash transfers system in 2019.[13]

We obtain our estimates by simulating potential income losses at the household level using the updated ENIGH. The simulations first

[11] The National Laboratory of Public Policies (*Laboratorio Nacional de Políticas Públicas*, LNPP, in Spanish) of the Center for Economic Research and Teaching (*Centro de Investigación y Docencia Económicas*, CIDE, in Spanish) which monitors the economic measures that the states have adopted in the face of the pandemic shows that out of the 32 states, 14 states have implemented direct transfer programs to respond to the crisis (https://lnppmicrositio.shinyapps.io/PoliticasEconomicasCOVID19/). According to a database collected by Cecilia Soto in Mexico, seven states (Chihuahua, Guanajuato, Jalisco, Nuevo Leon, Mexico, Mexico City, and Yucatan) spent around 0.7 percent of GDP as of July 2020 (email sent to Nora Lustig on August 31, 2020).

[12] 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).

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

identify individuals whose income is "at risk" because they work in sectors in which the COVID-19 pandemic have reduced or eliminated activity. We base our determination of at-risk income on the economic sectors in which one works. We assume that income derived from work in sectors that are "essential" is not at risk, while any income earned in "nonessential" sectors is at risk. For Mexico we use the ILO definition of essential sectors.[14] At the household level, the at-risk incomes also include rental incomes and incomes of informal street vendors (regardless of the sector in which they work). We aggregate this at-risk income at the household level.

Regarding incomes that are not-at-risk, besides including all the employment not counted as at risk according to the above definitions, we make two additional assumptions. First, incomes from cash transfers programs, consumption of own production, imputed rent, social security pensions, public employment, and private transfers (e.g., remittances) are not affected. Second, we do not consider the income of white-collar workers who are CEOs, managers and researchers with internet access at home to be at-risk even if they work in nonessential sectors.[15]

Figure 1 shows the composition of *per capita* household income by centile of the pre-crisis income (*per capita*) distribution across seven categories: cash transfers, consumption of own production, imputed rent, social security pensions, government salaries, other incomes not-at-risk, and incomes at-risk. This is shown at the national level and disaggregated by urban and rural areas. The population in urban areas, defined as those living in localities with 2,500 inhabitants or more, represents 75.5 percent of the country's total population.

[14] See *ILO Monitor:* COVID-19 *and the world of work*, available at: https://www.ilo.org/global/topics/coronavirus/impacts-and-responses/WCMS_749399/lang–en/index.htm. The distribution of employment between at-risk and not-at-risk by sector can be found in table A2 of Lustig *et al.* (2020).

[15] This assumption is supported by the findings from Garrote Sanchez *et al.* (2020). Their results show that better paid workers are less vulnerable to the labor market shocks from COVID-19 as they are more likely to be able to work from home. CEOs, managers and researchers belong to the group of better-paid workers.

Figure 1
Composition of per capita household gross income

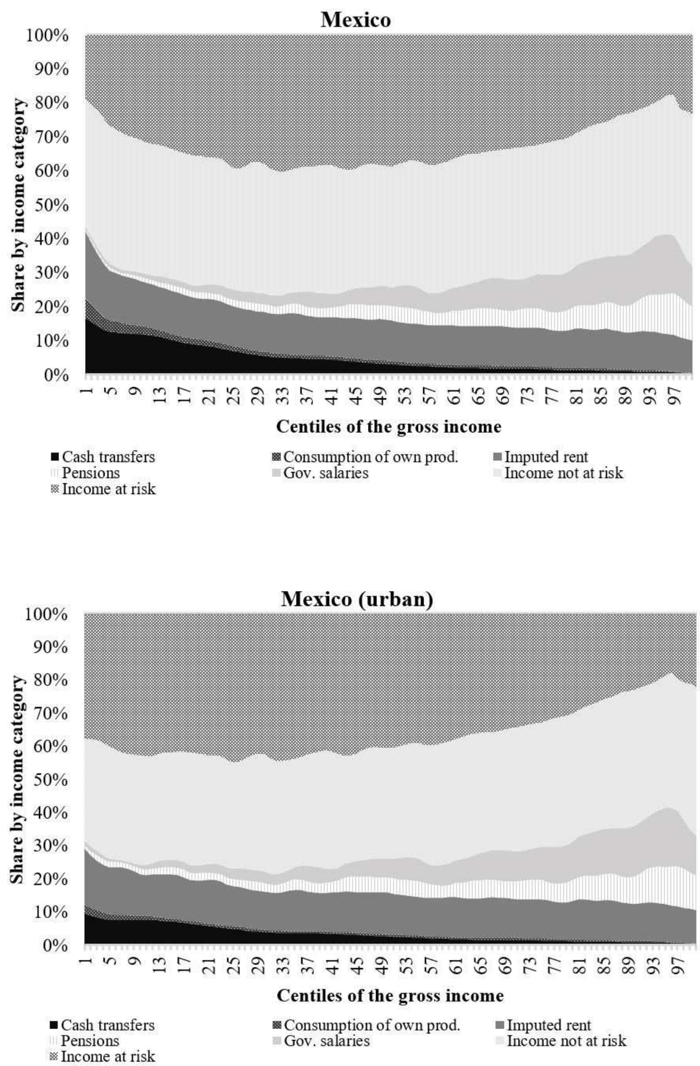
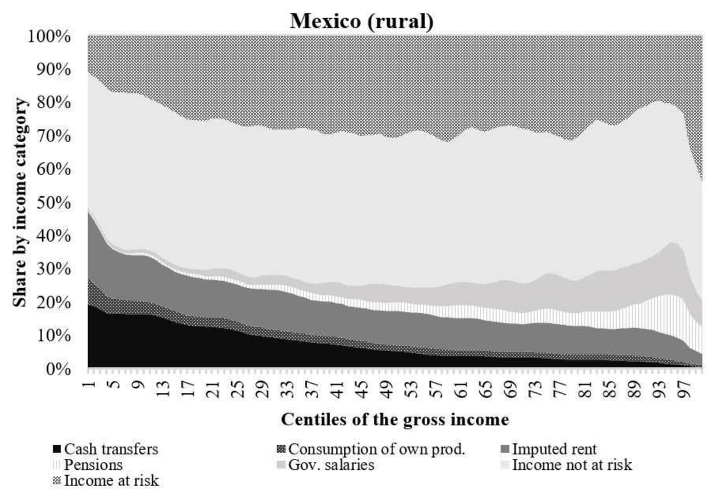


Figure 1
(continued)



Notes: Rural is defined as a locality with less than 2,500 inhabitants; 24.5 percent of the population is rural. Source: Authors' calculations based on ENIGH (2018).

There are several results to note. First, the share of income that is not at risk 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. The very poorest households have an income floor (albeit low) that protects an important share of their income. This income floor comes from three sources: cash transfers, consumption of own production, and imputed rent. Consumption of own production is especially notable in rural areas.

After at-risk income is identified, we 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 actually 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 (in 10 percent intervals), yielding a ten-by-ten matrix of possible income losses (table 1).

Table 1
Income losses matrix (as % of total gross income)

% 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	1.4	1.6	1.9	2.2	2.5	2.7
20%	0.6	1.1	1.7	2.2	2.8	3.3	3.9	4.4	5.0	5.5
30%	0.8	1.7	2.5	3.4	4.2	5.0	5.9	6.7	7.5	8.4
40%	1.1	2.2	3.4	4.5	5.6	6.7	7.8	9.0	10.1	11.2
50%	1.4	2.8	4.2	5.6	7.0	8.4	9.8	11.2	12.6	14.0
60%	1.7	3.4	5.2	6.9	8.6	10.3	12.1	13.8	15.5	17.2
70%	2.0	4.1	6.1	8.2	10.2	12.3	14.3	16.4	18.4	20.5
80%	2.3	4.7	7.0	9.3	11.6	14.0	16.3	18.6	20.9	23.3
90%	2.6	5.2	7.8	10.4	13	15.6	18.2	20.8	23.4	26.0
100%	2.9	5.8	8.7	11.6	14.5	17.4	20.3	23.1	26.0	28.9

Notes: Cells in gray correspond to losses similar to the loss projections by IMF (2020); cells in dark gray correspond to the "concentrated losses" and "dispersed losses" scenarios described in the text.

Source: Authors' calculations based on ENIGH (2018).

Cells in table 1 show the range of possible *per capita* gross income losses (as a proportion of *ex-ante* gross income) of all households 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-20 percent cell of this matrix, we show the fall in income in percent corresponding to the case in which 10 percent of the households (with at-risk income) lose 20 percent of their income each (and so on). The possible losses are very wide indeed, ranging from near zero to near 30 percent of pre-crisis income. For macroeconomic consistency, we narrow our focus to outcomes that have income losses similar to the IMF's October 2020 World Economic Outlook projections for the decline in GDP *per capita*, highlighted in gray in table 1.[16] From that "iso-loss" curve, we choose two scenarios: either a smaller proportion of households lose much income, or a larger proportion of households lose smaller

[16] We use the IMF predictions for 2020 adjusted to *per capita* growth rates using data on population growth for the latest year available. Then, following the method suggested by Ravallion (2003) and applied by Lakner *et al.* (2020), we assume a "pass-through" of GDP growth to household (gross) income growth of 0.85.

amounts of income. In the selected "concentrated losses" scenario, 30 percent of households lose 100 percent of their income while in the "dispersed losses" scenario, 100 percent lose 30 percent.

3. Results

Impact on inequality

We use the Gini coefficient to measure the impact on inequality. Table 2 shows the difference between the *ex-ante* and *ex-post* income Gini coefficients. As expected, the estimated increase in inequality is larger under the "concentrated losses" scenario than in the "dispersed losses" scenario. In the former, a smaller proportion of households are losing almost all their at-risk income which shifts them far to the lower end of the income distribution, necessarily increasing inequality almost regardless of where they started. In the latter, each losing household's loss is smaller and so less likely to move a large number of households to the low end of the distribution.

Table 2
Gini coefficient

Group	*Ex-ante*	*Ex-post*	*Change*
Concentrated losses	0.452	0.490	0.037
Dispersed losses	0.452	0.465	0.013

Notes: Change is in Gini points.
Source: Authors' calculations based on ENIGH (2018).

Impact on poverty

We estimate the incidence of poverty using two poverty thresholds: the national poverty line and the US $5.50 a day international poverty line (in 2011 purchasing power parity).[17] Table 3 shows the change in

[17] The national poverty line in 2011 PPP a day is equivalent to $7.8 in Mexico.

poverty from *ex-ante* income to *ex-post* income.[18] Given the size of the shock, it is not surprising that the estimated increases in poverty are very large for all poverty lines and scenarios. For both poverty lines, the results at the national level are quite similar across scenarios, suggesting that our results are robust to any particular pair of loss probability and loss share chosen from table 1 so long as they produce a national decline in income *per capita* similar to the IMF's projections for GDP. Overall, the increase in the number of poor (measured with the national poverty line) could be between 7.5 and 8.7 million. In contrast, a distribution-neutral simulation would result in an increase of 6.8 million individuals.

Table 3 presents the results for the change in poverty for *ex-ante* and *ex-post* income distributions by geographic area, and by ethnicity and gender of the household head. The impact of the economic dislocation on rural areas is potentially much less severe than for urban areas for both poverty lines and both scenarios. Because the indigenous population is concentrated in rural areas, the increase in poverty is lower for the indigenous than for the non-indigenous population. These results are closely related to the fact that, as shown in figure 1, households in rural areas have a larger income floor as a share of their *ex-ante* gross income. The increase in poverty seems to be broadly similar between male and female-headed households, especially for the national poverty line.[19]

Table 3
Incidence of poverty
Panel (a) "Concentrated losses"

Group	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (a) Headcount (National Poverty Line)				
National	45.6	51.7	6.0	7.5

[18] The results presented in this paper do not necessarily coincide with those shown in Lustig *et al.* (2020) because we use a different definition of the household gross income. In this paper, we added consumption of own production and imputed rent.

[19] The somewhat surprising result that *ex-ante* poverty is higher for male-headed households is a consequence of the fact that in Mexico a portion of female-headed households are households whose male wage earner is a migrant in the United States (or a richer urban area in Mexico). These households receive income from remittances that can be quite significant.

Table 3
(continued)

Group	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (a) Headcount (National Poverty Line)				
Urban	43.6	49.8	6.2	5.9
Rural	52.0	57.3	5.3	1.6
Indigenous	70.4	74.2	3.8	0.4
Non-Indigenous	43.5	49.7	6.2	7.1
Female	43.8	49.6	5.9	1.8
Male	46.3	52.3	6.0	5.7
Panel (b) Headcount ($5.5 PPP Poverty Line)				
National	27.4	35.1	7.7	9.6
Urban	19.4	27.9	8.4	8.0
Rural	51.7	57.1	5.3	1.6
Indigenous	58.8	63.4	4.6	0.5
Non-Indigenous	24.6	32.5	7.9	9.1
Female	24.6	31.6	7.0	2.2
Male	28.3	36.2	7.9	7.4

Panel (b) "Dispersed losses"

Group	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (a) Headcount (National Poverty Line)				
National	45.6	52.6	6.9	8.7
Urban	43.6	51.1	7.5	7.1
Rural	52.0	57.3	5.3	1.6
Indigenous	70.4	75.5	5.1	0.5
Non-Indigenous	43.5	50.6	7.1	8.2
Female	43.8	50.5	6.7	2.1
Male	46.3	53.3	7.0	6.6

Table 3
(continued)

Group	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (b) Headcount ($5.5 PPP Poverty Line)				
National	27.4	34.1	6.8	8.5
Urban	19.4	26.7	7.2	6.8
Rural	51.7	57.1	5.4	1.7
Indigenous	58.8	64.8	6.1	0.6
Non-Indigenous	24.6	31.4	6.8	7.8
Female	24.6	30.9	6.3	2.0
Male	28.3	35.2	6.9	6.5

Notes: Rural is defined as a locality with less than 2,500 inhabitants. The indigenous population includes individuals who responded that they speak an indigenous language. Change in poverty is in percentage points.

Source: Authors' calculations based on ENIGH (2018).

In sum, our exercise predicts an increase in the number of poor between 7.5 ("concentrated losses") and 8.7 ("dispersed losses") millions. Compared to other studies, our estimates are lower than ECLAC (2020) which estimates an increase of 9.5 million poor people (using the national poverty line). Our estimates are also lower than the National Council for the Evaluation of Social Development Policy (*Consejo Nacional de Evaluación de la Política de Desarrollo Social*, CONEVAL, 2020) which predicts an increase in the number of poor between 8.9 and 9.8 million. Hufmann and Najera (2020) predict an increase in the number of extreme poor between 13 and 16 million. Because we do not estimate the number of poor with the extreme poverty line, we are unable to compare our results with theirs.

Table 4 presents the test of the sensitivity of our poverty estimates to two assumptions: the definition of at-risk income and the size of the aggregate contraction. First, we replicate the results assuming that all labor income (except for government salaries) is at risk. Overall, the increase in the number of poor (measured with the national poverty line) could be between 7.2 and 8.3 million (to be compared with the simulations shown in table 3: 7.5 and 8.7 million). Second, we increase the aggregate contraction of GDP to 11.6 percent (an increase of 3 percentage points) and find that the increase in the number of poor (measured with the national poverty line) could be between 10 and 13 million.

Table 4
Sensitivity analysis of the incidence of poverty
Panel (a) "Concentrated losses"

Sensitivity Analysis	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (a) Headcount (National Poverty Line)				
All income is at risk	45.6	51.4	5.8	7.2
Shock +3 higher	45.6	53.7	8.0	10.0
Panel (b) Headcount ($5.5 PPP Poverty Line)				
All income is at risk	27.4	34.0	6.6	8.3
Shock +3 higher	27.4	37.7	10.4	13.0

Panel (b) "Dispersed losses"

Sensitivity Analysis	*Ex-ante*	*Ex-post*	*Change*	*New poor (in millions)*
Panel (a) Headcount (National Poverty Line)				
All income is at risk	45.6	51.5	5.8	7.3
Shock +3 higher	45.6	55.0	9.3	11.6
Panel (b) Headcount ($5.5 PPP Poverty Line)				
All income is at risk	27.4	32.9	5.5	6.9
Shock +3 higher	27.4	37.2	9.8	12.3

Notes: Change in poverty is in percentage points.
Source: Authors' calculations based on ENIGH (2018).

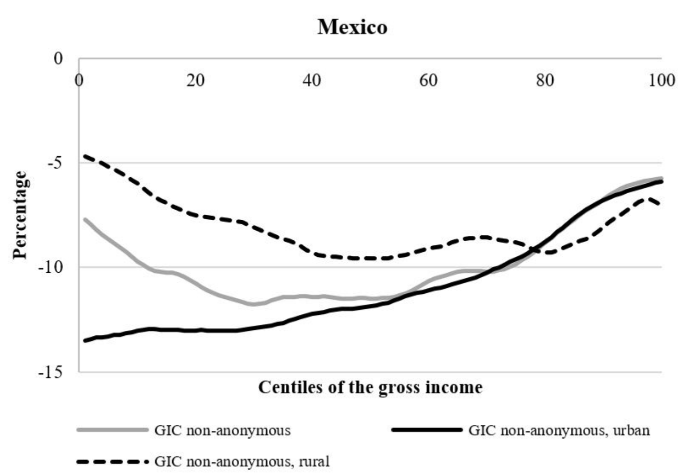
Impact on income mobility

The inequality and poverty 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 the non-anonymous growth incidence curves (GIC).[20]

We estimate that households across the entire income distribution could be worse off on average (regardless of the scenario) after the COVID-19 impact, which is not surprising (figure 2). We find that the worst effects may not be on the poorest, but those (roughly) in the middle deciles of the *ex-ante* income distribution: the moderate poor and those vulnerable to falling below the poverty line if subject to an adverse shock. This result does not downplay the negative effect of the economic crisis on poor households. Even if poorer households lose less in relative terms, the impact on living standards could be devastating, especially for the extreme poor.[21]

Figure 2

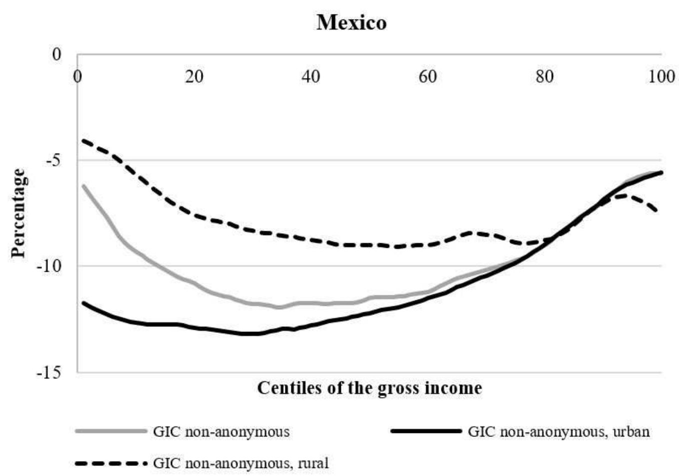
Non-anonymous growth incidence curves
Panel (a) "Concentrated losses"



[20] Bourguignon (2011) discusses the theoretical and practical differences between the standard anonymous comparisons and non-anonymous GIC.

[21] See Wagstaff (1986) and Lustig (2000).

Panel (b) "Dispersed losses"



Source: Authors' calculations based on ENIGH (2018).

The trajectories, however, could be quite different for rural in comparison to urban areas. The black lines in figure 2 show the GIC after the effect of the COVID-19 crisis for urban (solid line) and rural (dashed line) areas. First, except for the top, the fall in incomes is lower for rural areas throughout the distribution and for either scenario. The reason why households in the top (10 or 20 percent, depending on the scenario) fare better in urban areas is associated with the larger share of incomes from public employment and pensions, two sources assumed to remain unaffected. The larger participation of incomes from agricultural employment, consumption of own production, and cash transfers in rural areas explains why for the rest of the distribution rural areas are hit less. Second, within each area, the poorest urban households are actually among those who get hurt the most. In contrast, for rural areas the impact is U-shaped. The latter reflects that poorer households in rural areas have a larger share of their income coming from social assistance and consumption of own production (figure 1).

4. Conclusions

Our microsimulations show that the potential impact of the economic dislocation on inequality and poverty can be quite large. In addition, contrary to many people's priors, the non-anonymous growth incidence curves show that income losses could be more pronounced for the moderate poor and those vulnerable to falling below the poverty line rather than among the poorest. This is so because social assistance programs and consumption of own production represent a larger share of total gross income for the poorest, especially in rural areas. In essence, these two items put a "floor" for the incomes of the poorest of the poor (the poor in rural areas). The economic dislocation is likely to cause a smaller increase in poverty for rural areas because it is here where consumption of own production -as a share of gross income- is the largest. Because the indigenous population is concentrated in rural areas, the rise in poverty among the indigenous population is potentially lower than for the non-indigenous one. The expected rise in poverty is similar for male and female-headed households.

Lustig *et al.* (2020) estimate the increase in poverty due to the COVID-19-induced economic dislocation in Argentina, Brazil, Colombia, and Mexico. Their estimates suggest that Brazil and Mexico could face the largest increase in the number of poor among these countries. However, they also find that the expanded social assistance governments have introduced in response to the crisis could have a large offsetting effect in Brazil and Argentina. In Colombia, the mitigation is quite modest. In Mexico, it is nil: the Federal government has provided no (at least, not as of the writing of this article) additional social assistance in the wake of the crisis.

Acknowledgments

This paper draws from N. Lustig, V. Martinez Pabon, F. Sanz and S. D. Younger (2020). The Impact of COVID-19 Lockdowns and Expanded Social Assistance on Inequality, Poverty and Mobility in Argentina, Brazil, Colombia and Mexico, *COVID Economics: Vetted and Real-Time Papers*, Issue 46, Center for Economic Policy Research (CEPR). However, in contrast to the former, we include two additional sources of income: consumption of own production and imputed rent. In addition, we carry out the analysis not only at the national level but also by urban and rural areas. The authors are grateful to Raymundo Campos and John Scott for their very useful suggestions. 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, see: http://www.ceqinstitute.org.

Nora Lustig: nlustig@tulane.edu; Valentina Martínez Pabón: vmartinezpabon@tulane.edu

References

Bottan, N.L, D.A. Vera-Cossio, and B. Hoffmann. 2020. The unequal impact of the coronavirus pandemic: Evidence from seventeen developing countries, IADB Working Paper Series No. 1150.

Bourguignon, F. 2011. Status quo in the welfare analysis of tax reforms, *Review of Income and Wealth*, 57(4): 603-621.

Brussevich, M., E. Dabla-Norris, and S. Khalid. 2020. Teleworking is not working for the poor, the young, and the women, IMF Blog.

Busso, M., J. Camacho, J. Messina, and G. Montenegro. 2020. The challenge of protecting informal households during the COVID-19 pandemic: Evidence from Latin America, IADB Discussion Paper No. 780.

CONEVAL. 2020. La política social en el contexto de la pandemia por el virus SARS-CoV-2 (COVID-19) en México, Ciudad de México, CONEVAL.

ECLAC. 2020. Addressing the growing impact of COVID-19 with a view to reactivation with equality: New projections, Special Report COVID-19 No. 5.

Figari, F., A. Paulus, and H. Sutherland. 2015. Microsimulation and policy analysis, in A.B. Atkinson and F. Bourguignon (eds.), *Handbook of Income Distribution*, Vol. 2, 2143-2221, Elsevier.

Garrote Sanchez, D., N. Gomez Parra, C. Ozden, B. Rijkers, M. Viollaz, and H. Winkler. 2020. Who on earth can work from home? Policy Research Working Paper No. 9347, World Bank.

Gerszon, D., C. Lakner, A. Castaneda, and H. Wu. 2020. Updated estimates of the impact of COVID-19 on global poverty, World Bank Blogs.

Hufmann, C. and H. Nájera. 2020. Estimación del costo de eliminar la pobreza extrema por ingreso en México en tiempos de COVID, Programa Universitario de Estudios del Desarrollo, UNAM. http://www.pued.unam.mx/opencms/difusion/pobreza.html.

IMF. 2020. World economic outlook update, June 2020, https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020.

INEGI. 2018. Encuesta nacional de ingresos y gastos de los hogares (ENIGH) 2018, https://www.inegi.org.mx/programas/enigh/nc/2018/.

INEGI. 2020. Resultados de la encuesta telefónica de ocupación y empleo (ETOE), cifras oportunas de junio de 2020, https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2020/enoe_ie/ETOE2020_08.pdf.

Lakner, C., D.G. Mahler, M. Negre, and E.B. Prydz. 2020. How much does reducing inequality matter for global poverty? Global Poverty Monitoring Technical Note No. 13, World Bank.

Lustig, N. 2000. Crises and the poor: Socially responsible macroeconomics, *Economía*, 1(1): 1-30.

Lustig, N., V. Martinez-Pabon, F. Sanz, and S.D. Younger. 2020. The impact of COVID-19 lockdowns and expanded social assistance on inequality, poverty and mobility in Argentina, Brazil, Colombia and Mexico, *COVID Economics: Vetted and Real-Time Papers*, 46(1): 32-67, Center for Economic and Policy Research.

Pages, C., C. Aclan, M. Alfonso, R. Arroio, J. Irigoyen, I. Mejía, C. Mendieta, S. Moreno, A. Muente, S. Peñaherrera, C. Pombo, F. Regalia, W. Savedoff,

E. Stein, and L. Tejerina. 2020. From lockdown to reopening: Strategic considerations for the resumption of activities in Latin America and the Caribbean within the framework of COVID-19, Washington D.C., IADB Monograph No. 814, Inter-American Development Bank.

Ravallion, M. 2003. Measuring aggregate welfare in developing countries: How well do national accounts and surveys agree? *Review of Economics and Statistics*, 85(3): 645-652.

Universidad Iberoamericana. 2020. Resultados actualizados de la "Encuesta de seguimiento de los efectos del COVID-19 en el bienestar de los hogares mexicanos", Comunicados.

Wagstaff, A. 1986. The demand for health: Theory and applications, *Journal of Epidemiology & Community Health*, 40(1): 1-11.

World Bank. 2020. Macro poverty outlook: Country-by-country analysis and projections for the developing world.