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From Middle Class to Poverty

The Unequal Impacts of the COVID-19 Pandemic on Developing Countries

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1. Introduction

The COVID-19 pandemic and the associated containment measures led to dramatic declines in economic activity levels and disrupted labor markets worldwide, with potentially large distributional impacts. Empirical evidence from developed and developing countries is showing that traditionally disadvantaged workers --women, young, and low-educated workers—were hit hardest by the pandemic and, as a consequence, the patterns of existing inequalities are being exacerbated (Adams-Prassl et al., 2020; Fairlie et al., 2020; Lee et al., 2021; Kugler et al., 2021).

Workers in developing countries are often self-employed or working in informal arrangements with a relatively low earnings level. The containment measures particularly affect these groups of workers, leading to decreasing incomes and higher chances of falling into poverty. To design effective policies to protect the most vulnerable segments of the population, the distributional impacts of the pandemic need to be known. In the longer term, the calculations of prompt estimates on how individuals and households are affected during any crisis are crucial inputs for timely policy responses.

During the COVID-19 pandemic, different sources of data and methodological approaches have been used to estimate the distributional impacts of the crisis. In particular, phone surveys gained momentum during the pandemic as an instrument to gather information on the ground while respecting social distancing and lockdown policies. Phone surveys successfully collected information on respondents' employment status and their perception of whether their household income declined, remained the same, or increased (Khamis et al., 2021; Kugler et al., 2021). A quite different approach to estimate the distributional impacts is through Computable General Equilibrium models using different scenarios of GDP reduction and transmission mechanisms, such as in the ILO (2020) and Vos et al. (2020) studies. In addition, some studies adjust pre-pandemic poverty lines using different scenarios of per capita income or consumption contraction or, alternatively, actual information on per capita GDP reduction (Sumner et al., 2020; Diop and Asongu, 2020). But these methodologies make strong distributional or structural assumptions, which lead the results to be sensitive to the choice of methodology.[2]

In this study we follow a different approach, which applies a macro-micro simulation that combines pre-COVID-19 household surveys microdata with 2020 data on sectoral employment levels, sectoral GDP, private consumption, and remittances. With this information, we simulate the transmission of the COVID-19 shock via three channels – job loss, labor income declines, and changes in remittances— on household per capita income (or consumption) and the shares of poor, vulnerable, and middle-class populations in each country during 2020. We present projections for

[2] For example, ILO (2020) projects that, using the 3.2 USD-a-day poverty line, the number of poor workers in 2020 will increase between 8.8 million and 35 million persons in 138 low- and middle-income countries compared to pre-COVID-19 estimates. Sumner et al. (2020) project short-term increases in poverty of between 85 million and 580 million persons with respect to 2018 values for more than 150 countries using different poverty lines. Vos et al. (2020) predict an increase of between 12 million and 22 million in the number of extreme poor people (1.9 USD-a-day poverty line) in 30 countries of mainly Sub-Saharan Africa and South Asia in 2020. For 50 African countries, Diop and Asongu (2020) show increases of between 19 million and 26 million additional poor people in 2020 using different poverty lines.

five developing countries during 2020 –Brazil, Sri Lanka, the Philippines, South Africa, and Türkiye.

The objectives are threefold. The first is to understand the extent to which employment projections based on GDP elasticities may be biased during a crisis. Changes in employment levels are a key input into these macro-micro models. When employment data is not available, projections of job gains or losses are needed, and these are often based on employment-to-GDP elasticities. The second objective is to better understand the projected distributional impacts of the economic shock during the first year of the pandemic in five countries from different regions of the world. Finally, the third objective is to better understand in Brazil, where post-crisis data on shock magnitudes exist, the extent to which the proposed methodology generates accurate estimates of the distributional impacts of the shock.

The combination of pre-COVID-19 microdata with National Accounts data from 2020 to estimate 2020 poverty rates is similar to other studies (ECLAC, 2020; Brum and De Rosa, 2021; World Bank, 2021). The methodology used here differs from these studies in two respects. First, we use a different procedure than in ECLAC (2020) and Brum and De Rosa (2021) to simulate changes in individual and household labor incomes. In particular, similar to World Bank (2021), we predict an individual probability of becoming unemployed, as a function of both sector of employment and formality status.[3] Second, we differ in the consideration of government transfers and work from home possibilities. Unlike several other studies, our study does not include changes in government transfers in the simulation of household income changes, due to lack of information across all the countries under study here and thus to maintain comparability.[4] As such, it predicts total income changes, poverty rates, and shares of vulnerable and middle-class populations that can be attributed to job losses, labor income changes, and changes in remittances.

We proceed by, first, presenting an in-depth analysis of employment elasticity projections for 15 developing countries selected based on the availability of post-crisis employment data from Labor Force Surveys or other official sources. The sample includes 5 countries from the Europe and Central Asia region, 6 from Latin America and the Caribbean, 3 from East Asia and Pacific, and one from Sub-Saharan Africa. When no employment data is available, employment elasticities are a crucial input to project employment changes and simulate the distributional impact of a shock. However, these estimates may provide biased inputs during a crisis period and, especially, during the recent pandemic when large drops in GDP were observed. Employment projections based on elasticities may overestimate the employment loss, for instance, because most countries have implemented crisis-relief measures such as cash transfers and wage subsidies that may have protected employment but not been reflected in GDP growth. We therefore use pre-COVID-19 data on GDP and employment levels to perform a sensitivity analysis using different model specifications. The projected employment levels are then compared with observed 2020 values. The differences or biases between actual and projected employment levels are correlated with the

[3] For example, some studies do not distinguish the job loss channel by sector of activity (Brum and De Rosa, 2021) or assign the probability of losing a job exogenously (ECLAC, 2020). The former, however, consider amenability of working from home when predicting job loss.

[4] Brum and Da Rosa (2021), World Bank (2021), and ECLAC (2020) include government transfers in the simulation of household income changes.

stringency of the social distancing measure, a mobility measure, and a measure of scale-up of cash transfer programs at the country level to understand what is behind the lack of precision in some of the specifications.

Second, we apply a macro-micro simulation methodology in five countries that combines pre-COVID-19 household surveys with national accounts data for 2020. The methodology follows the household income generation model proposed by Bourguignon and Ferreira (2005), and instead of using a CGE model or macro projections to go from macro changes to micro impacts, we use actual 2020 data on employment level, sectoral GDP, private consumption, and remittances. The results of the simulation are used to project changes in household per capita income or consumption by quintiles between 2019 and 2020, changes in poverty rates at different lines, and changes in the shares of the vulnerable population and middle class.

Third, we compare the changes in poverty, vulnerable population, and middle class obtained using actual 2020 employment data in the macro-micro simulation methodology versus using employment projections based on the calculation of employment elasticities.

Finally, we validate our estimations for Brazil using 2019 and 2020 microdata from the PNAD-Contínua. Using this survey, we calculate actual poverty rates and poverty rates excluding incomes from emergency assistance programs implemented since the pandemic started. This allows us to isolate the poverty changes that are explained by the job loss, labor income, and remittance channels.

Our results can be summarized as follows:

(i) In most countries, employment estimates for 2020 based on elasticities were reasonably accurate. The projected levels of employment are within 5 percent of the actual levels in 11 of the 15 countries. However, in four countries the projections significantly overestimated employment levels and therefore underestimated job loss due to the crisis. This bias tends to be larger (i) for labor markets that were more disrupted by the pandemic as measured by the stringency of social distancing measures, changes in workplace mobility, and a measure of scale-up of cash transfer programs, and (ii) in the agriculture sector in comparison to the industry and service sectors.

(ii) The simulations show declines in the per capita household income or consumption across the entire distribution. However, the impacts across the distribution varied across countries, with no clear pattern. In Sri Lanka and Brazil, for example, the simulations project larger shocks for poorer households. In Türkiye, the changes are similar across income groups. In the Philippines, the simulated reductions were largest for households in the middle three quintiles, while in South Africa, the simulated reductions were largest for the top three quintiles. When using employment projections based on elasticities instead of actual employment data, the projected income declines were smaller in all countries and quintiles.

(iii) Actual 2020 micro data for Brazil shows that the simulations underestimated the magnitude of the shock throughout the distribution, especially for the wealthy, because they underestimated the earnings declines, and thus underestimated the increase in poverty. The underestimation is even larger when using employment projections based on elasticities instead of 2020 employment levels as inputs in the microsimulation.

Overall, the results are mixed. Estimates based on employment elasticities were reasonably accurate in most countries, although generally in the direction of overestimating employment, but they tended to be less accurate in countries with higher disruptions in the labor market. Furthermore, in the five countries considered, the macro-micro simulation methodologies capture differences in the structure of the labor market and the macroeconomic impact of the shock that led to clear differences in the projected distributional impacts. The results overall show that the middle class declined, and poverty increased for all five countries in 2020, under a scenario that did not incorporate new emergency public transfers as mitigation measures. In Brazil, however, the simulation methodology considerably underestimated the extent of (pre-transfer) income losses, suggesting that these macro-micro simulations require additional fine-tuning of the assumptions so as to: (a) allow for a reduction in hours and a corresponding reduction in earnings that occurred as part of countries' programs protecting employment stability; and (b) take into account that the exclusion of the emergency public transfers from the model would imply that a larger private consumption shock needs to be applied in the model.

The rest of the paper is organized as follows. Section 2 presents the projections of 2020 employment levels using different employment elasticity models. Section 3 presents the macro-micro simulation methodology and main results, while Section 4 discusses robustness checks and a validation exercise. Section 5 concludes.

2. The importance of employment elasticities and their estimation

The elasticity of employment to GDP seeks to capture the responsiveness of labor markets to changes in macroeconomic conditions. Elasticity estimates may provide biased projections of employment levels during a crisis period when large drops in GDP are observed. For instance, in countries without labor protection mechanisms such as unemployment insurance, workers may reallocate to self-employment or to the informal sector to avoid being unemployed.

We hypothesize that elasticity-based estimates would overestimate employment loss during the pandemic crisis for three reasons. First, GDP growth fell dramatically. Product losses have been unusually large for countries that depend on tourism and commodity exports and for those with limited policy space to respond (IMF, 2021). GDP losses during 2020 were as high as 11% in Spain (European region), 9.5% in the Philippines (Asian region), 8.2% in Mexico (North America), 30% in the República Boliveriana de Venezuela (South America), 25% in Lebanon (Middle East and Central Asia), and 7% in South Africa (Sub-Saharan Africa) (IMF, 2021). If the employment elasticity itself depends on the extent of the GDP loss, then an elasticity measure derived during normal years may not be accurate during shock periods. Second, most countries have implemented crisis-relief measures including cash transfers, wage subsidies and labor regulation adjustments (Gentilini et al., 2021; World Bank, 2021; ILO, 2020). Some of these measures, such as wage subsidies, may have protected employment but not been reflected in GDP growth. Third, the crisis may have reduced productivity more than employment through the disruption in supply chains in many industries and the implementation of social distancing policies that reduced mobility and promoted remote work.[5]

In this section we obtain estimates of employment elasticities for the agriculture, industry, and services sectors using different model specifications. Using these elasticities, we project the level of employment for 2020 and compare them against actual employment data. We cover 15 countries in four regions. The sample includes Albania, Bulgaria, North Macedonia, Romania, and Türkiye from the Europe and Central Asia region; Brazil, Colombia, Costa Rica, Ecuador, Mexico, and Peru from Latin America and the Caribbean; Indonesia, the Philippines, and Vietnam from East Asia and the Pacific, and South Africa from Sub-Saharan Africa. These countries were selected based on the availability of post-crisis employment data from Labor Force Surveys or other official sources.

To calculate employment elasticities, we use data on sectoral employment and sectoral GDP levels for the period 2010 to 2018[6] from ILO and World Development Indicators, respectively. To project the 2020 employment level, we use the 2019 employment level from ILO and the 2020 estimated GDP change from the World Bank's Macro Poverty Outlooks. Finally, we compare our employment projections with actual data on 2020 employment levels from National Statistical Offices.

2.1 Employment elasticity models and results

We compare estimated elasticities from six different estimation methods. These models are estimated for each country separately. First, we calculate sectoral *average elasticities*. The average sectoral elasticities are defined as the average among annual elasticities obtained as the ratio between the percentage change of employment and the percentage change of GDP between consecutive years. Second, we calculate sectoral *average elasticities without outliers* by excluding from previous calculations those annual elasticities which fall outside of a bound defined as Q_1-(1.5*IQR) and Q_3+(1.5*IQR), where Q_1 and Q_3 are the first and third quartiles of the annual elasticities and IQR is the interquartile range. Third, we apply a *mean regression* method to obtain sectoral point elasticities by estimating OLS models of the logarithm of employment on the logarithm of GDP. Fourth, we calculate sectoral employment elasticities by estimating *median regression* models. Fifth, we expand the mean regression method by adding the logarithm of total GDP as a control variable to consider the fact that sectoral employment levels depend not only on the sectoral GDP but also on the movements of the economy as a whole. Last, we expand the mean regression method by including the logarithm of total GDP multiplied by the sectoral informality rate as a control variable. The objective is to control for the fact that in some of the countries in

[5] The available evidence on the relationship between home-based work and productivity is not conclusive. Studies finding a negative association have indicated that reduced uninterrupted working hours at home, some tasks not being able to be performed at home, poor telecommunication environment, and loss of face-to-face interaction with coworkers are the main reasons for productivity reductions (Behrens et al., 2021; Gibbs et al., 2021).

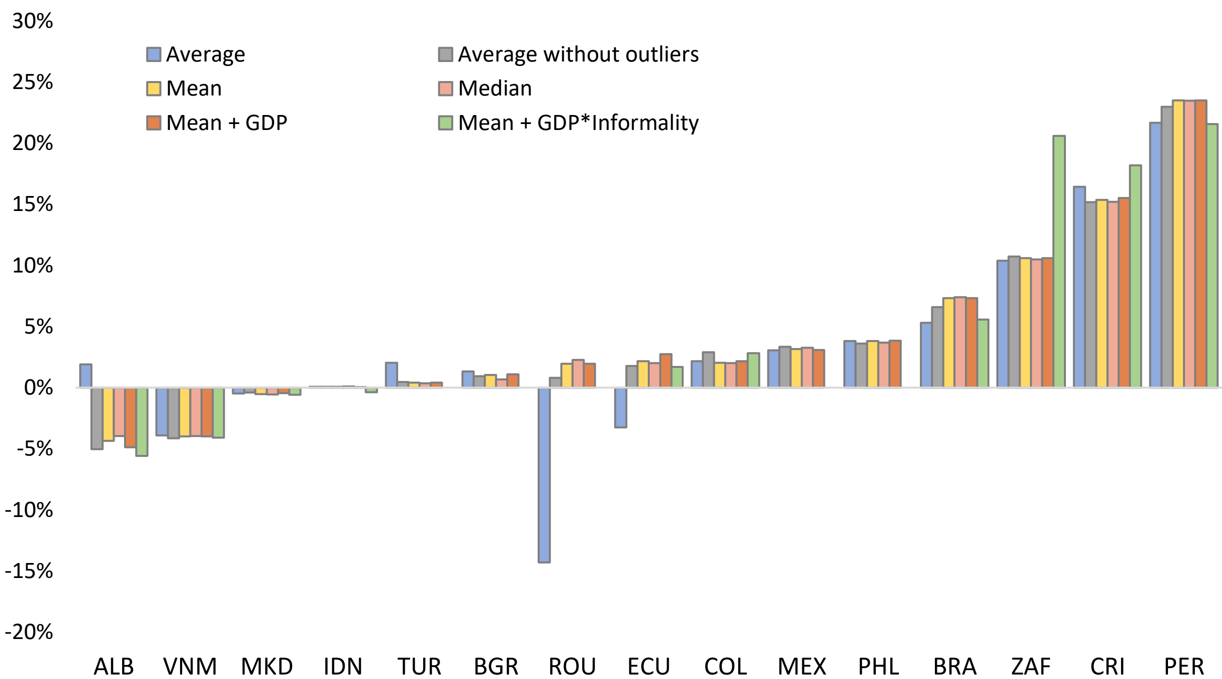
[6] At the time of undertaking the work to estimate the employment elasticities, the 2019 data was not yet available and 2018 data was the latest available. Nevertheless, it is not expected that the elasticities will differ much.

our sample, labor informality is a pervasive phenomenon that may operate as a buffer mechanism during a crisis.[7]

Having estimated the sectoral elasticities, we project the 2020 employment level for each country and sector. To obtain these projections, we use ILO data for 2019 sectoral employment levels and estimated sectoral GDP changes from the World Bank's Macro Poverty Outlooks. We then add the sectoral projections within each country and obtain an estimation of the total employment level for 2020 that we compare with the observed employment level reported by National Statistical Offices.[8]

Figure 1 presents, for each country and method, the percentage difference between our employment level projection for 2020 and the observed employment level.

Figure 1. Percentage difference between 2020 employment projections and actual 2020 employment levels



Notes: The mean regression method controlling for the logarithm of GDP interacted with the informality rate is not available in Bulgaria, Mexico, the Philippines, Romania, and Türkiye. Actual 2020 employments levels come from National Statistical Offices. The exact data of actual 2020 employment data is shown in Table A1 in the Appendix.

[7] Bulgaria, Mexico, the Philippines, Romania, and Türkiye are excluded from this sixth method due to lack of data on labor informality.
[8] The date of the observed 2020 employment level differs between countries depending on the information available in National Statistical Offices. Table A1 in the Appendix contains information on the exact date considered in each country.

Five main findings emerge from this figure:

(i) In most countries, the employment projections tend to overestimate the actual employment level of 2020, and therefore underestimate the magnitude of the employment contraction. This is contrary to our expectation that employment projections would overestimate employment losses as explained above.

(ii) The magnitude of the bias of the employment projections differs greatly between countries, ranging from close to zero for some countries and methods, such as Indonesia, to more than 20%, as in Peru when using any of the elasticity methods.

(iii) Within each country and with only some exceptions, there is little difference in the performance of the different elasticity methods, resulting in employment projections' biases of similar magnitude. Exceptions include Albania, Türkiye, Romania, and Ecuador, in which the average elasticity method performs more poorly than the others, and South Africa, where using the mean regression method controlling for GDP interacted with labor informality leads to less accurate estimates.

(iv) In 11 of the 15 countries, the differences between actual and projected 2020 employment levels were less than 5%, regardless of the method and direction of the bias, while in 4 countries the differences were larger than 5%. The first group includes Albania, Vietnam, North Macedonia, Indonesia, Türkiye, Bulgaria, Romania, Ecuador, Colombia, Mexico, and the Philippines. The second group includes Brazil, South Africa, Costa Rica, and Peru.

(v) The most accurate method differs between countries. In Albania, Brazil, Mexico, South Africa, and Vietnam, the best method is the average of annual elasticities. In Costa Rica, North Macedonia, the Philippines, and Romania, it is the average elasticity without outliers. In Bulgaria, Colombia, and Türkiye, the best method is the median regression. In Indonesia, it is the mean regression controlling for the logarithm of total GDP. Finally, in Ecuador and Peru, the method with the best performance is the mean regression controlling for the logarithm of total GDP interacted with the informality rate. Table A2 in the Appendix shows the percentage difference between our employment projection for each country and method and the actual employment level, highlighting the method with the best performance. In general, the mean regression, median regression, and the average without outliers methods perform well in all cases. In many cases, there is little difference between the performances of the different methods.

In Figure A1 in the Appendix, we present the comparison between the employment projections for 2020 and the observed employment levels disaggregating by country, estimation method and economic sector.[9] We find that the magnitude of the bias is larger in the agriculture sector in 8 of 14 countries regardless of the estimation method and direction of the bias. In 4 countries, the bias is larger in the service sector, while in the remaining two countries, the largest biases appear in the industry sector. Another important finding to highlight is that in 8 of the 14 countries included in the analysis, the direction of the bias differs between sectors. In four of these 8 countries, the sector where the elasticity estimations lead to a bias of a different sign is the agriculture sector. In Costa Rica, Peru, Philippines, and South Africa, the bias for the agriculture sector is negative, meaning

[9] Sectoral employment data for 2020 is not available for Albania.

that the projected employment level for this sector is lower than the observed employment level in 2020. For the industry and service sectors, the estimation bias is positive in these four countries.

All in all, the sectoral employment projections based on elasticity estimations tend to be more biased for the agriculture sector, and when the direction of the bias differs between sectors, agriculture is the one behaving differently in most cases. This pattern could be related to the differential impact of non-pharmaceutical measures, such as mobility restrictions, across sectors. For instance, agriculture was considered an essential sector in some countries because of its role in food production. As such, the sector continued performing some of its production activities despite the confinement measures. In the next subsection we explore the association between the magnitude of the estimation biases and government non-pharmaceutical measures for the aggregate.

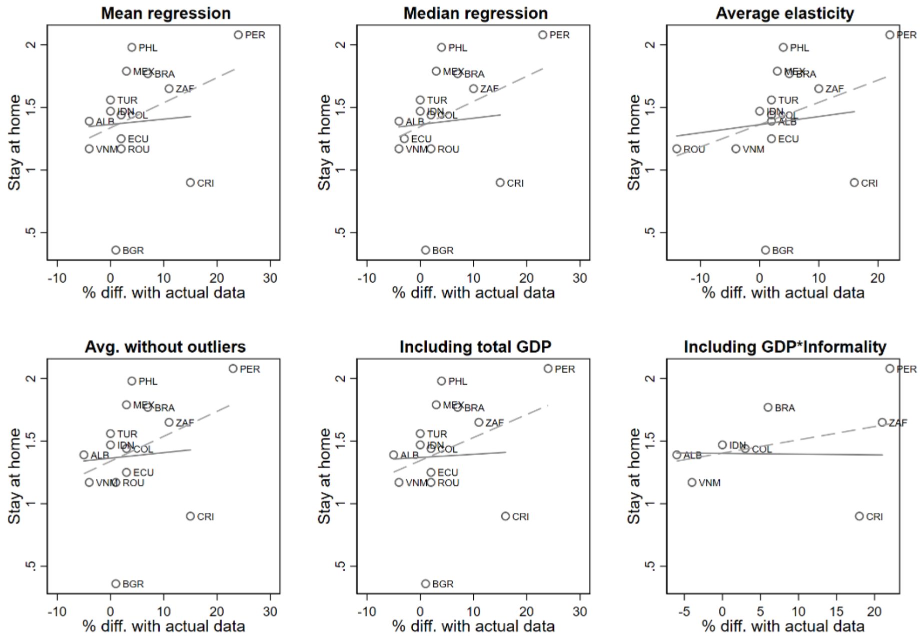
2.2 Explaining the bias in employment projections

The large biases found for some of the countries and methods are related to the distinctive features of the COVID-19 crisis. The implementation of lockdown measures meant dramatic reductions in economic activity. Most governments implemented social protection measures which can protect employment in some cases and distort incentives to work in some others.

In order to explore the association between bias in the employment projections and the distinctive characteristics of the pandemic crisis, we use information on government non-pharmaceutical measures from the Oxford COVID Tracker, i.e., the severity of stay-at-home orders, changes in workplace mobility from Google mobility data, and a measure of government social protection policies from Gentilini et al. (2021).

The stay-at-home order from the Oxford COVID Tracker ranges from 0 to 4 with a higher value indicating stricter requirements. We calculate the average of the stay-at-home order for each country using daily information from March 15 to December 31 of 2020. The correlation between the stay-at-home order and the bias of our employment projections appears in Figure 2. For all the elasticity methods we find a positive association between the stringency of the stay-at-home requirements and the percentage differences between our employment projections for 2020 and actual 2020 employment levels. In other words, pre-crisis employment elasticities estimates are more likely to underestimate employment losses in countries with more stringent stay-at-home orders. This may be because more stringent stay-at-home requirements led to additional job losses that were not reflected in GDP growth estimates, making the elasticity of employment with respect to growth greater than it usually would be. When excluding Peru from the sample –the country with the largest difference between our 2020 employment projection and the observed value, we still find positive associations between the bias and the stay-at-home orders, although smaller in magnitude.

Figure 2. Correlation between the bias in employment level projections and stringency of the stay-at-home orders

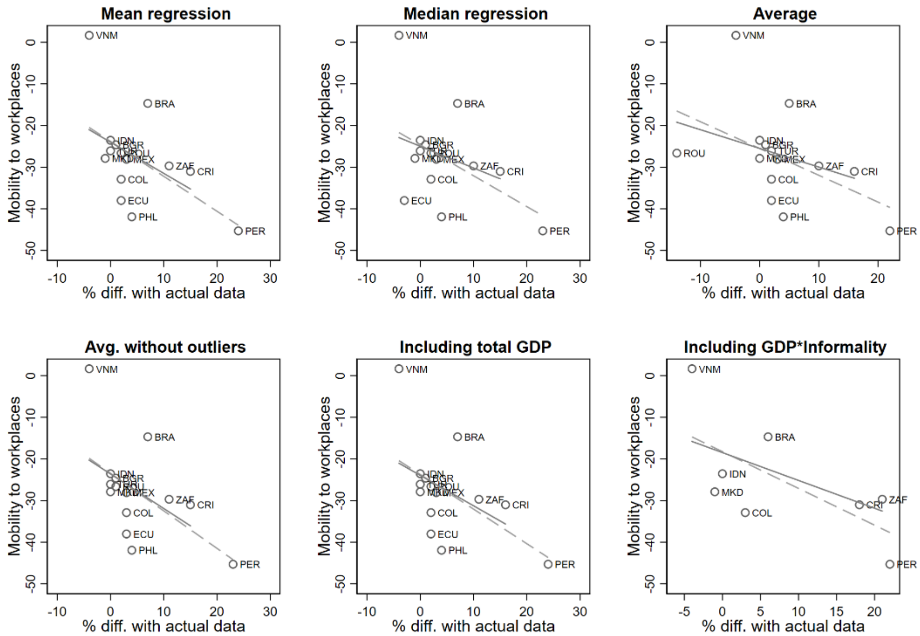


Notes: The stay-at-home measure is not available for North Macedonia. Dashed lines show the correlation using all countries, while solid lines exclude Peru.

Next, we present the correlation between the biases of the employment level projections and a measure that captures the change in mobility to workplaces. This measure comes from Google's COVID-19 Community Mobility Reports and was obtained from OurWorldInData. This measure captures the change in the number of visitors compared to a baseline value.[10] We take the average of this measure from March 15 to December 31 of 2020. Results appear in Figure 3 and show that in countries where mobility to workplaces declined the most, employment projections were more likely to overestimate employment levels and underestimate employment losses. This is consistent with the prior result on the stringency of stay-at-home orders and reflects the obvious negative correlation between stringency and mobility.

[10] Baseline days are defined as the median value for the 5-week period from January 3 to February 6, 2020.

Figure 3. Correlation between the bias in employment level projections and changes in mobility to workplaces

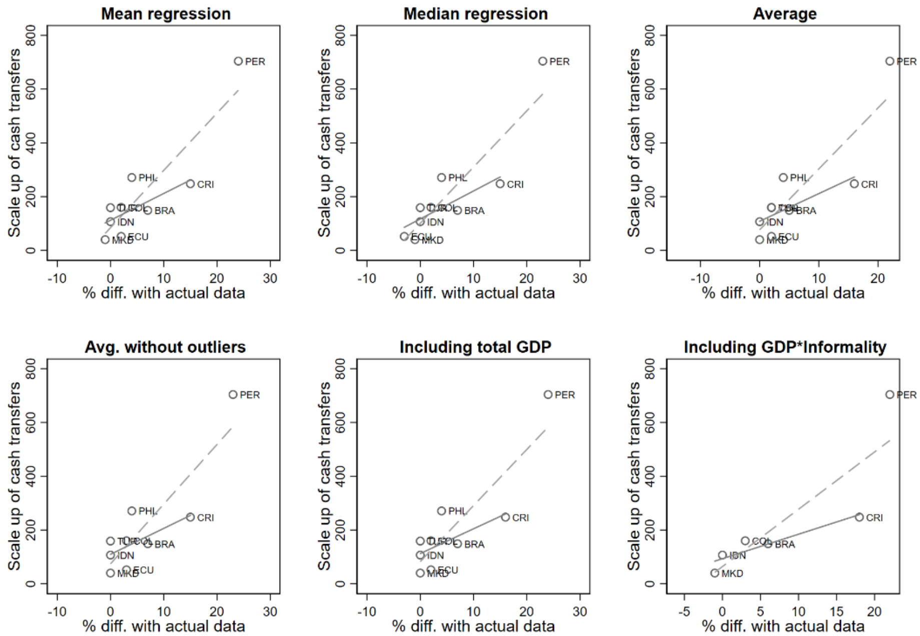


Notes: The mobility to workplaces measure is not available for Albania. Dashed lines show the correlation using all countries, while solid lines exclude Peru.

In Figure 4 we analyze the correlation between the bias of our employment projections and a measure of government social protection during the pandemic. This measure comes from Gentilini et al.'s (2021) study and captures the scale-up of cash transfers relative to pre-COVID levels. The figure shows a positive correlation indicating that countries with larger expansions of cash transfer programs are more likely to overestimate employment levels and underestimate the full extent of job loss. Excluding Peru from the sample does not affect the positive association. An important consideration regarding these positive correlations is that larger scale-up transfers may be behind greater job losses due to a reduction in incentives to work. But it could also be the case that countries with more stringent non-pharmaceutical measures (such as mobility restrictions) were more likely to scale up transfers to compensate for the effects of these measures. The correlation between the scale-up of cash transfers and changes in mobility to workplaces is negative, indicating that this might have been the case.[11]

[11] The correlation between scale-up cash transfers and changes in mobility to workplaces is -0.59 and statistically significant while it drops to -0.26 when excluding Peru from the sample. These negative correlations mean that larger reductions in mobility to workplaces were accompanied by larger expansions in cash transfers.

Figure 4. Correlation between the bias in employment level projections and scale-up of cash transfer programs during COVID-19



Notes: The scale-up measure is not available for Albania, Bulgaria, Mexico, Romania, Vietnam, and South Africa. Dashed lines show the correlation using all countries, while solid lines exclude Peru.

All in all, countries where our 2020 employment projections have a poor performance are those where labor markets seem to have been disrupted the most by the pandemic.

2.3 Comparison with employment elasticities from a previous recession

To further analyze the accuracy of the estimated employment elasticities, we generate, for each country and economic sector, employment elasticities for the period 2006-2009. This period encompasses the Great Recession and captures the reaction of employment levels to GDP changes during a crisis.

We estimate sectoral average elasticities and elasticities applying the mean regression method explained before using sectoral employment and GDP data for the period 2006-2009.[12] We then compare the results with the estimated elasticities and estimated employment levels for 2020 presented in Section 2.1. We use data for the same set of countries except for Vietnam where sectoral GDP data is not available.

Using the average elasticities method, we find the elasticities for the period 2010-2018 are higher than those estimated for the period of crisis (2006-2009) in 50% of the cases. In 33% of the cases

[12] Data on sectoral employment and sectoral GDP comes from the World Development Indicators.

the estimated elasticities have different signs, and when the sign is the same, the average difference between the 2010-2018 period and the 2006-2009 period is 315%.

For the mean regression method, we find that elasticities estimated for the period 2010-2018 are above the values of the 2006-2009 period in 21% of the cases. The estimated elasticities differ in their sign in 29% of the cases and when the sign is the same, the average difference between the 2010-2018 period and the 2006-2009 period is 69%.

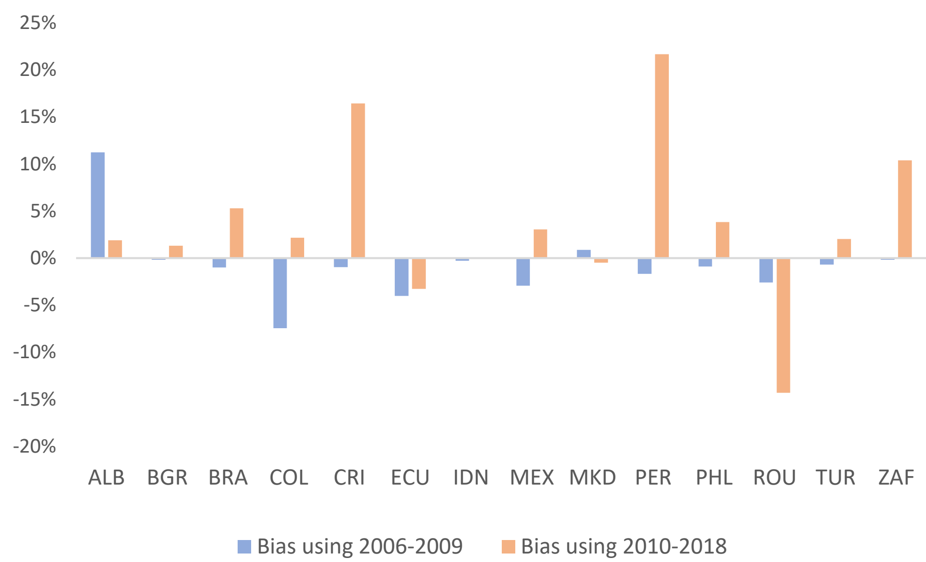
When then compare the bias (percentage difference) between 2020 employment projections and actual 2020 employment levels using elasticities for the 2006-2009 period versus the 2010-2018 period. The comparisons appear in Figure 5-Panel A. For the average elasticities method, we find that while elasticities estimated for the 2010-2018 period tend to overestimate the employment level of 2020, the elasticities of the 2006-2009 period tend to underestimate it. In 9 of the 14 countries, the estimated elasticities for the period 2006-2009 perform better –the bias is smaller.

When using the mean regression method, we find that with only a few exceptions the employment projections are very close regardless of using the 2006-2009 or 2010-2018 periods for estimating employment elasticities. The comparison of the bias indicates that in 2 of the 14 countries they are the same using both periods (Indonesia and South Africa). For the remaining 12 countries, elasticities estimated using the 2006-2009 period perform slightly better in 9 of them.

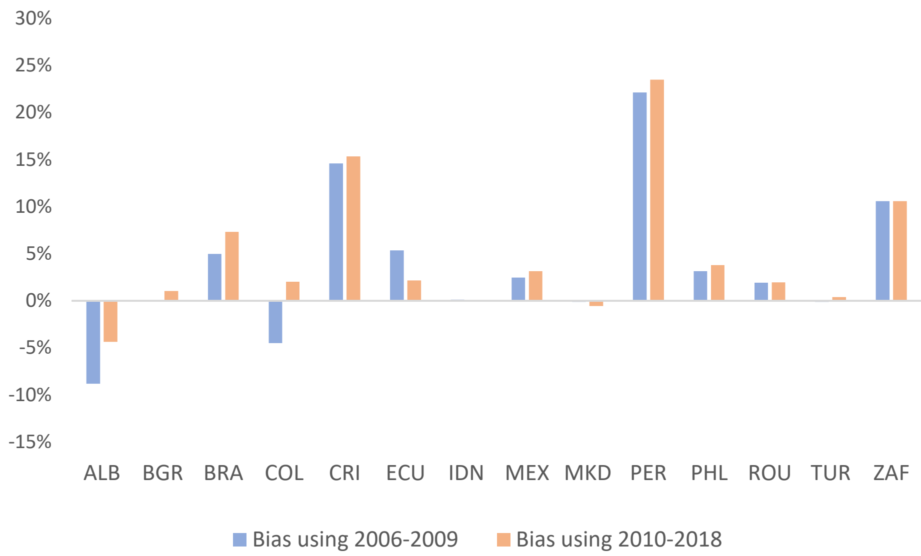
This exercise indicates that using estimated employment elasticities from a crisis period generates smaller biases in the projection of employment levels. However, depending on the method used, the estimated biases do not differ much from using a non-period crisis.

Figure 5. Percentage difference between 2020 employment projections and actual 2020 employment levels. Comparison between estimation periods

Panel A. Average elasticities



Panel B. Mean regression



Notes: Actual 2020 employments levels come from National Statistical Offices. The exact data of actual 2020 employment data is shown in Table A1 in the Appendix.

3. Microsimulations

This section turns to the microsimulations themselves. We use actual employment changes taken from the ILO as an input into the microsimulation models. We use the elasticity-based estimates as a robustness check. Whenever possible, these models should use actual available employment data, but when that data is not yet available, analysts would have to use employment projections. The macro-micro simulation model applies country-specific macroeconomic projections to a behavioral model built on household survey microdata. The microsimulations are based on a household income generation model (Bourguignon and Ferreira 2005), while the macro data come from a variety of macroeconomic projections in combination with observed data for 2020 obtained from different data sources for each country. The macro-micro model allows for three main channels of transmission of the 2020 shock: through job losses, labor income changes, and non-labor (remittance) income changes. Having estimated (or used actual) labor and remittances income changes, we predict the household per capita income or consumption value for 2020 and we calculate the shares of poor, vulnerable, and middle class in each country.

We apply this model to five countries in five regions: Brazil, the Philippines, South Africa, Sri Lanka, and Türkiye.[13] The model requires five main inputs. Country-specific household survey microdata for each country is based on the 2019 Pesquisa Nacional por Amostra de Domicilios-Continua for Brazil; the 2018 Household Income and Consumption Expenditures Survey for Türkiye; the 2018 Family Income and Expenditure Survey for Philippines; the 2016 Household Income and Expenditure Survey for Sri Lanka; and the 2019 General Household Survey for South

[13] We select the countries according to the availability of labor force surveys (for the measurement of employment level in 2020) and a household survey (for poverty measurement in 2019) with data on income and remittances.

Africa. Projected annual growth rates in Private Consumption per capita from National Expenditure Accounts are provided by World Banks' Macro Poverty Outlooks. Sectoral GDP growth projections in Agriculture, Industry, and Services are provided by the International Monetary Fund's World Economic Outlook Reports. Observed employment level for 2020 comes from the International Labor Organization for Brazil, Sri Lanka, and South Africa, from OECD for Türkiye and from government estimates for the Philippines. Projected changes in remittances by country are obtained from World Banks's Migration and Remittances Data. Another input is a set of population projections for 2019 and 2020 based on the World Banks' Macro Poverty Outlooks.

3.1 Methodology

The model takes the household surveys microdata mentioned above as a starting point. The methodology then allows three main channels of transmission of the 2020 shock: through job losses, labor income changes, and non-labor (remittance) income changes.

Job losses or gains in Agriculture, Industry, and Services in 2020 are taken from observed employment levels from the ILO, OECD, or government estimates and compared to household survey data from previous years. When employment data is not available for a specific year, then job losses or gains by sector, by country, are estimated using elasticity estimates, such as those presented in Section 2. In that case, sectoral GDP growth projections (in Agriculture, Industry, and Services) are combined with the elasticities to provide employment projections.

These job losses/gains per sector then need to be imposed onto the household survey data. To match the new expected 2020 employment levels in each sector, the model has to determine which individuals in the base year household survey will lose (or gain) jobs to reach this new target. A Probit model, applied to each of the three sectors and by formal and informal workers, provides each person in each household survey a probability of employment:

$$Pr\left(Y_i^{csf} = 1 \middle| X\right) = \varphi(X_i^{csf}\beta)$$

where i is a person, c is a country, s is a sector (agriculture, industry, or services) and f is the formality status (formal or informal). X includes sex, age, education level, urban/rural, dependency rate, dummy for member working in public sector, and a dummy for remittances.[14] Workers are ranked by the predicted probability of employment, and those with the lowest employment probability are simulated to lose their job, until total job loss matches the employment projections (or actual values when known) for job loss by sector. For job gains, new workers are chosen among the unemployed according to the probability of being employed in that sector until total job gains match the employment projections by sector (or the actual values when known).

The second main channel of transmission of the 2020 shock is through labor income changes. Workers who are simulated to lose their job experience year-long unemployment and 100% cuts in labor income. In the case of job gains, a new labor income is estimated via a traditional Mincer equation, in which the logarithmic of income is regressed on sex, age, education level, urban/rural,

[14] The indicator variable of urban area is available for Brazil, South Africa, Sri Lanka, and Türkiye.

dependency rate, and a dummy indicating if the household has income from remittances. Workers who are employed in Public Administration, Utilities, Health, or Extraterritorial Agencies are protected from facing any job losses or income changes.[15] For all workers that retain their jobs but are not employed in the protected sectors (Public Administration, Utilities, Health, and Extraterritorial Agencies), their labor incomes are adjusted up or down by a single scale factor equal to the percentage change in private consumption per capita of their specific country in 2020.

Next, projected changes in remittances by country are also included in the microsimulations. The percent change in remittances at the national level is applied as a direct percent change in the remittance income of any household that receives this income in the household survey. Changes in other sources of non-labor income different from remittances are not considered because data was not available for all countries. Once all three channels of transmission of the shock are incorporated, household per capita income is calculated by summing up the final income of each household member and dividing by the total number of household members.

We derive the distributional impacts of COVID-19 exploiting heterogeneities in household characteristics in the microdata. The first source of heterogeneity is the difference in the composition of income per-capita by income source. Different shares from each source of income will imply a different effect of the macroeconomic projections for each household. For example, households that do not receive remittances are not affected by the economic shock on remittances. Similarly, household incomes that are derived from pensions, capital income, and public transfers are not affected by the economic shock.

The second source of heterogeneity is the sociodemographic characteristics across households. Households differ by gender of the head of household, by education levels of members, by household composition, etc. Different characteristics will predict a different probability to suffer an unemployment shock, or for those who gain employment their different characteristics will predict different new incomes.

The third source of heterogeneity is the sector of employment, as job losses by sector vary, whether according to macroeconomic projections or actual available data. Each country faces different sectoral GDP projections or estimates. Workers in four sectors are protected from any shock: Public Administration, Utilities, Health, and Extraterritorial Agencies.

This macro-micro simulation model provides several advantages over other methodologies. First, it allows estimating distributional impacts and not only poverty impacts. Second, the use of actual employment data when available (as opposed to using projected employment levels based on past elasticities) partially addresses the potential concern of using past data to predict outcomes, especially during an unprecedented crisis with unique elements, such as the implementation of mobility restrictions.

However, the model also faces some limitations. First, because of the unprecedented nature of the crisis, the estimation of employment probabilities based on pre-crisis household and individual characteristics may have limited predictive power. Second, the model is focused on average annual impacts to ensure consistency between the macro and micro projections. Consequently, it is

[15] This procedure is not applied in South Africa where there is no detailed information on sector of employment.

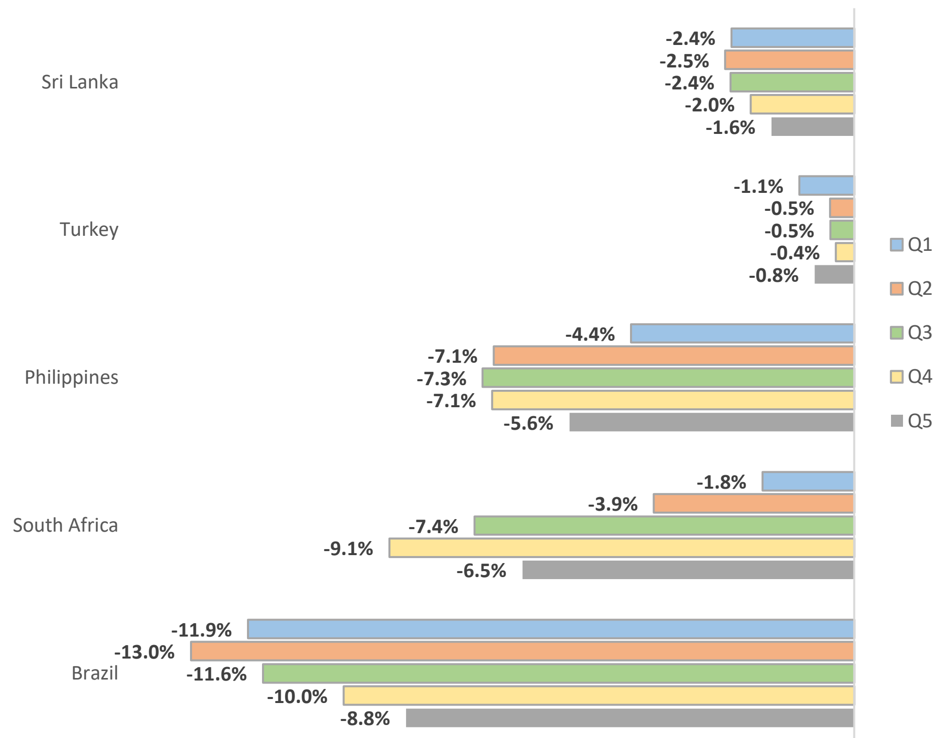
difficult to estimate quarterly or monthly impacts due to the lack of macro projections at this level. Finally, the model does not require sectoral reallocation because only the agriculture sector was growing in some countries during the period under analysis, but the method would need to be adjusted in cases where there are substantial job gains in multiple sectors.

3.2 Results

Projected income changes

Figure 6 presents our estimations of changes in average income or consumption per quintiles of the initial per capita household income/consumption distribution between 2019 and 2020.[16] In all countries analyzed there is a decline in the per capita household income/consumption across the entire distribution after the pandemic shock. The pattern of change –i.e., whether the bottom quintiles faced larger reductions than richer quintiles— differs on a country-by-country basis.

Figure 6. Projected average income changes between 2019 and 2020 per quintiles of the initial per capita household income distribution. In percentages



Notes: Projections following the methodology detailed in section 3.1. Estimates based on reported employment data. Estimates do not include changes in non-labor income.

[16] Table A3 in the Appendix presents the values of average per capita household income by quintiles.

In Sri Lanka and Brazil, there is a clear pattern between the magnitude and direction of income changes and the position in the initial income distribution. The first quintiles suffered larger income declines than the top quintiles. In Sri Lanka income changes range between -2.4% and -2.5% in quintile 1 to quintile 3, while the corresponding changes were -2.0% and -1.6% in quintiles 4 and 5, respectively. In Brazil, differences were larger with declines between -11.6% and -13.0% in quintiles 1 to 3, and reductions of -8.8% and -10.0% at the top (in a simulation that does not account for the generous emergency transfer program undertaken by the government of Brazil in 2020, which covered a large part of the population and protected the poorest from income loss).

In South Africa and the Philippines, middle- and top-income quintiles are the ones suffering the largest income declines. In South Africa, income declines range between -6.5% in quintile 5 and -9.1% in quintile 4. Bottom quintiles, on the other hand, suffered smaller income losses (-1.8% in quintile 1 and -3.9% in quintile 2). The Philippines exhibits a similar pattern. Income reductions are around -7% for quintiles 2 to 4, while it is -4.4% for quintile 1.

In Türkiye, income changes were very small for all quintiles of the per capita household income distribution. The smallest changes were between -0.4% and -0.5% in quintiles 2 to 4, while the largest change was a reduction of 1.1% in quintile 1.

Overall, the shock caused income declines across the distribution, but with no pattern across countries. This suggests that differences in the structure of the labor market captured by the household survey as well as the sectoral growth patterns taken from National Accounts lead to diverse patterns of projected distributional impacts. This would require further study.

We also study how income changes correlate with the educational level and occupation of the household head. Panel A of Table 1 shows that in four out of five countries —Türkiye, Philippines, South Africa, and Brazil—income losses were larger the lower the educational level of the household head. The magnitude of the losses, however, differ between countries. For instance, household where the head has up to complete primary education faced an average income loss of 8.3% in South Africa and of 11.6% in Brazil. For households where the head has tertiary education, the loss was of 6.3% in South Africa and 8.4% in Brazil. Sri Lanka is the only exception to the negative correlation between education of the household head and magnitude of the income loss. In this country, households where the head has up to complete primary education experienced an income increase, while households with more educated household heads faced income reductions.

Panel B of Table 1 presents income changes by initial occupation of the household head. We do not find a clear pattern in this case. For instance, in Philippines, households where the head was initially an unpaid worker or a wage employee suffered the largest income losses (10.6% and 7.8% respectively). In South Africa, the largest income losses were for households where the head was self-employed, unemployed or wage employee (19.1%, 7.5% and 7.3% respectively).

Table 1. Projected average income changes between 2019 and 2020 initial household head educational level and occupation. In percentages

	Sri Lanka	Turkey	Philippines	South Africa	Brazil
Panel A: By household head educational level					
Up to complete primary education	0.4%	-0.7%	-8.3%	-8.6%	-11.6%
Complete or incomplete secondary education	-1.6%	0.0%	-6.0%	-6.8%	-10.1%
Complete or incomplete tertiary education	-1.0%	0.0%	-4.5%	-6.3%	-8.4%
Panel B: By household head occupation					
Employer	-0.3%	-1.8%	-2.6%	-5.7%	-13.7%
Wage employee	-2.4%	0.0%	-7.8%	-7.3%	-10.7%
Self-employed	0.3%	-0.1%	-4.2%	-19.1%	-13.5%
Unpaid worker	-0.1%	0.8%	-10.6%	-5.9%	-10.0%
Unemployed	0.2%	-0.2%	-5.4%	-7.5%	-9.1%

Notes: Projections following the methodology detailed in Section 3.1. Estimates based on reported employment data. Estimates do not include changes in non-labor income.

Projected welfare changes

Figure 7 presents the 2019-2020 change in our projections for the poverty rates (using the international 2.25, 3.65 and 6.85 USD per day poverty lines in 2017 PPP), size of the vulnerable class (defined as a household per capita income between 6.85 and 13 USD a day in 2017 PPP), and size of the middle-class (defined as a household per capita income between 13 and 70 USD a day in 2017 PPP).[17] In general, we observe poverty rates increasing, as expected given the income declines across the entire income distribution. The share of the population that are vulnerable and middle class declined, indicating that a larger number of people exited these groups by becoming vulnerable or poor than entered from a more advantageous position.

In line with the projected average income changes discussed before, some of the largest poverty increases appear in Brazil, the Philippines, and South Africa. In Brazil, the 2.25, 3.65 and 6.85 USD a day poverty rates are expected to increase 2.7, 4.0 and 5.2 percentage points respectively, in a scenario without emergency transfers. These are substantial changes implying increases of between 20% and 47% in the poverty rates –for instance, the 2.25 USD-a-day poverty rate would have increased from 5.7% to 8.4%. Interestingly, the share of the vulnerable population is expected to decline in only 0.3 percentage points while the share of middle-class is projected to suffer a reduction of 4.3 percentage points (again in a scenario without the generous emergency transfer program).

In the Philippines, our projections show increases of 1.3 and 3.1 percentage points in the 2.25 and 3.65 USD-a-day poverty rates respectively, and a rise of 4.4 percentage points in the 6.85 USD-a-day poverty rate. These increases imply that the poverty rates will be between 10% and 31% higher in 2020 than in 2019 –for instance, the 2.25 USD-a-day poverty rate is expected to grow from 4.3% to 5.6%. The share of the vulnerable and the middle-class population is predicted to fall by 2.0 and 2.3 percentage points, respectively.

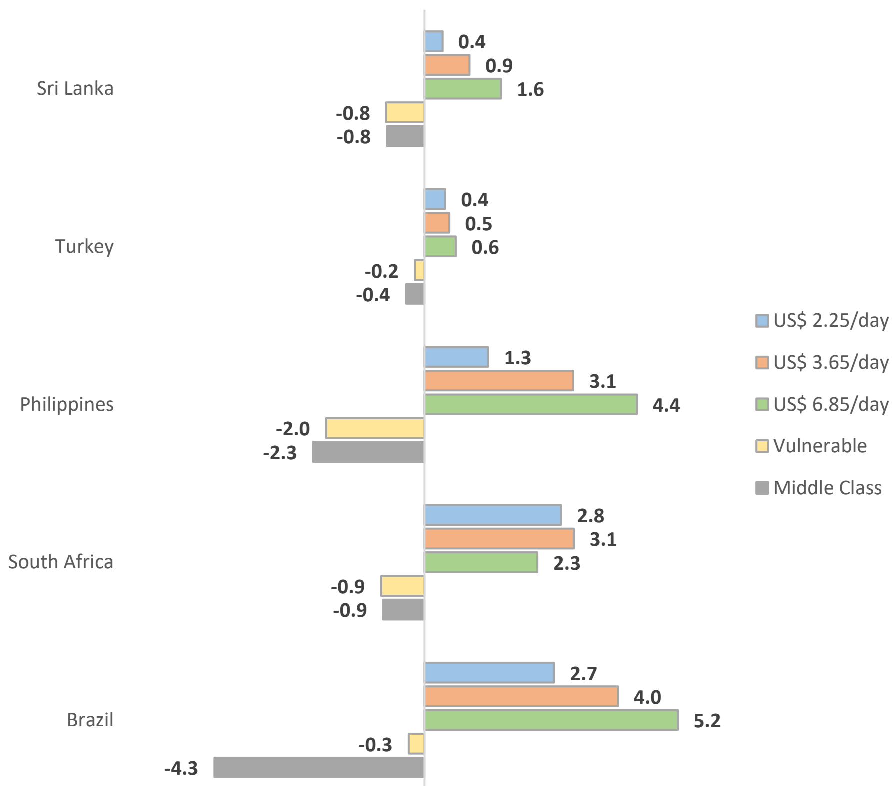
[17] Table A4 in the Appendix presents the estimated poverty, vulnerability, and middle-class rates.

In South Africa, our projections indicate that the 2.25, 3.65 and 6.85 USD a day poverty rates will increase in 2.8, 3.1 and 2.3 percentage points, respectively. The shares of both the vulnerable population and the middle-class are predicted to decline by -0.9 percentage points.

In Sri Lanka, the share of poor people is expected to increase between 0.4 and 1.6 percentage points between 2019 and 2020. These increases are explained by reductions in the shares of both vulnerable and middle-class people (-0.8 percentage points in both cases). In Türkiye, the expected changes in the shares of poor, vulnerable, and middle-class populations are small –between -0.2 and 0.7 percentage points—which is in line with the projected changes in average per capita household income.

In conclusion, the projected distributional impacts varied by country, but overall, the projections indicate that 2020 was characterized by downward economic mobility. The middle class declined across all five countries while poverty increased, with larger percentage point increases for the higher poverty lines.

Figure 7. Projected changes in poverty rates by poverty line and changes in the share of vulnerable and middle-class population between 2019 and 2020. In percentage points



Notes: Vulnerable defined as a household per capita income between 6.85 and 13 USD a day. Middle class defined as a household per capita income between 13 and 70 USD a day.

4. Robustness checks and validation

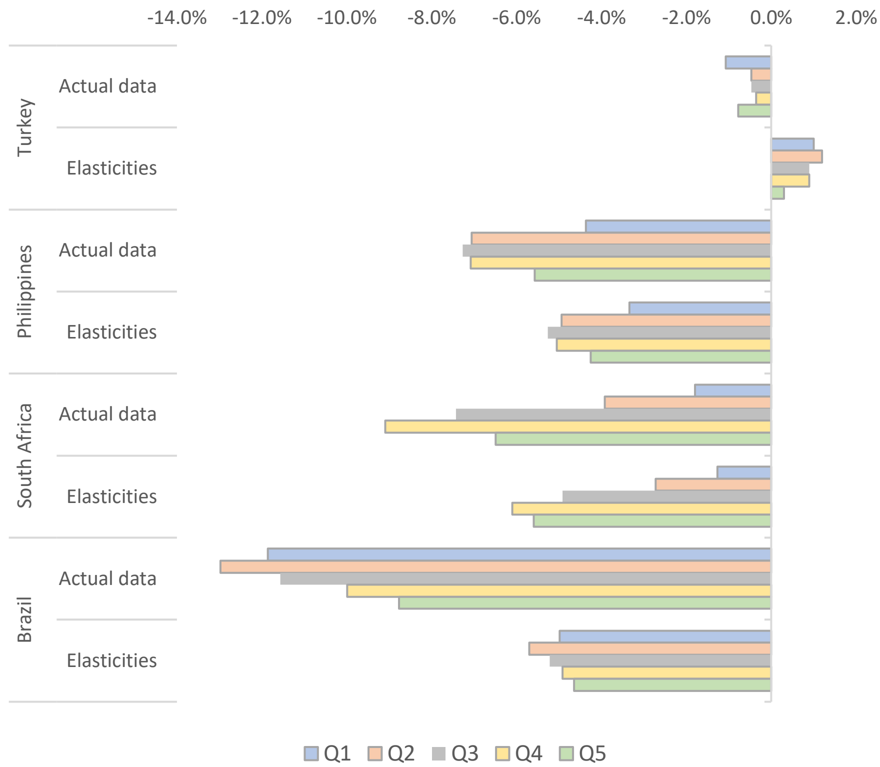
4.1 Robustness to use of projected employment declines

The results of the macro-micro simulation reported in the previous section used actual employment data, taken from the ILO, for 2020. In many settings, like at the outset of a crisis, employment data may not be available. In this robustness exercise we compare the poverty, vulnerability, and middle-class projections presented in Section 3.2 with another set of results obtained using the sectoral employment elasticities calculations of Section 2 to project the employment level of 2020. We perform this analysis for Brazil, the Philippines, Türkiye, and South Africa using the elasticity method with the best performance according to Table A2 in the Appendix.

As was previously discussed, the 2020 employment projections based on employment elasticity calculations tend to overestimate the actual employment level of 2020 and therefore underestimate the adverse impact of the crisis on employment. Although the overestimation of employment was on a reasonable range of 5% for some countries, for some others including Brazil and South Africa, it was above that level (see Figure 1). Depending on which part of the income distribution these "additional workers" are located, we could obtain different poverty projections with respect to the results presented before.

Figure 8 shows that when using employment levels based on elasticities projections, we obtain a similar pattern of income change across the entire distribution. The only exception is Türkiye where we obtain small income increases instead of small income declines. The magnitude of the income reductions, however, are smaller in comparison to using actual employment data. For instance, in Brazil our previous simulation results show a decline of 12% of the per capita income of the bottom quintile, while using elasticities the decline is 5%.

Figure 8. Changes in per capita household income between 2019 and 2020 by quintiles of the initial income distribution using different employment data. In percentages

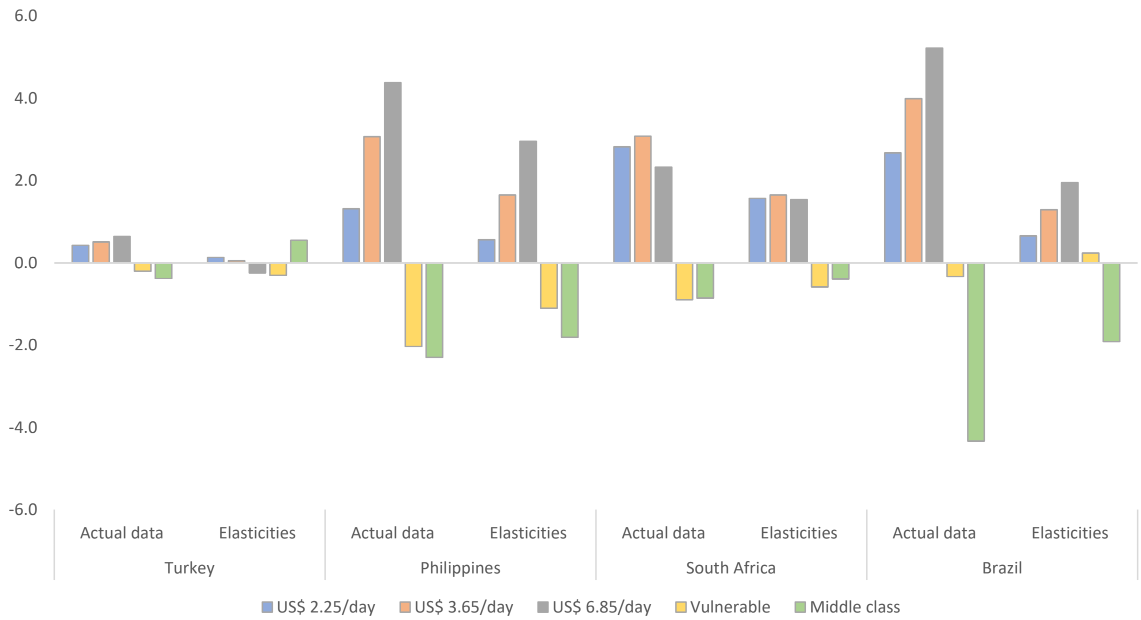


Notes: Projections following the methodology detailed in section 3.1. Estimates based on reported employment data. Estimates do not include changes in non-labor income.

Figure 9 compares changes in poverty, vulnerability, and the middle class between 2019 and 2020 when using the methodology of Section 3 and when using employment projections based on employment elasticities as an input in the macro-micro simulation model. The results indicate that the use of employment elasticities leads to: (i) smaller poverty increases and even poverty reductions in some cases (for instance, the share of people below the 6.85 USD-a-day poverty line in the Türkiye); (ii) smaller reductions in the share of the vulnerable population and increases in some cases (Philippines, South Africa and Brazil); and (iii) smaller reductions in the size of the middle class in some cases (Philippines, South Africa and Brazil) and a an increase in some other (Türkiye).

For Brazil specifically, the differences are substantial. Using 2020 employment data, our simulations project poverty increases ranging between 3 and 5 percentage points depending on the poverty line used. When using employment elasticities to project the employment level of 2020, the expected poverty increases are below 2 percentage point (between 25% and 40% of the poverty increases using actual employment data). The large differences in Brazil, however, are in line with the earlier findings that the employment-GDP elasticities were underestimating the magnitude of the employment contraction. In the Philippines and South Africa, on the other hand, poverty increases using employment elasticities range between 40% and 70% of the increases obtained using 2020 employment levels.

Figure 9. Poverty, vulnerable population, and middle-class projected changes between 2019 and 2020 using different employment data. In percentage points



Notes: Vulnerable defined as a household per capita income between 6.85 and 13 USD a day (2017 PPP). Middle class defined as a household per capita income between 13 and 70 USD a day (2017 PPP). Table A5 in the Appendix present the values of the estimated rates when using employment elasticities.

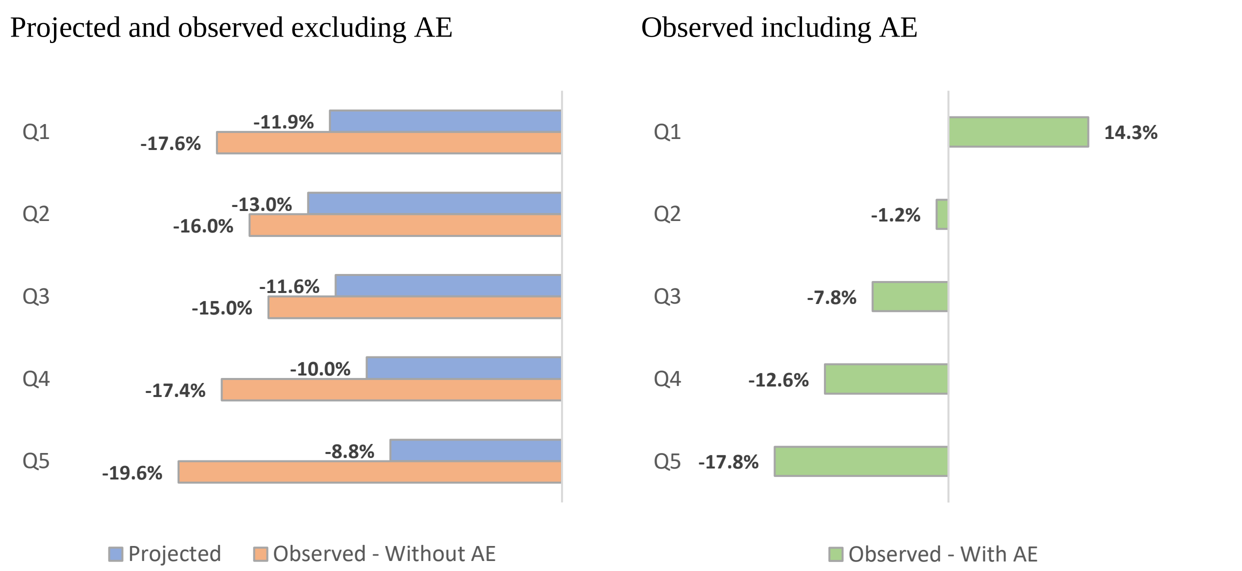
These results highlight the importance of using accurate employment data to simulate the distributional impacts of a shock.

4.2 Validation in Brazil

The availability of 2020 household survey data for Brazil allows us to test how close our previous simulations are from the observed poverty rates during 2020. Using data from the PNAD-C collected during 2020, we present a validation exercise where we compare our projections of the average changes in income between 2019 and 2020 by quintiles of the initial per capita household income with the observed values according to the PNAD-C. We present two calculations: the first one excludes the Auxilio Emergencial transfer program (because our macro-micro simulation methodology does not consider government transfers), and the other one includes this program as part of household income.

Our results appear in Figure 10 and show that the observed change in household income when excluding income from the Auxilio Emergencial followed a U-shaped pattern. This estimate was done with a panel of households (about three-fourths of the original data) that appear in both the 2019 and 2020 PNAD-C household surveys. The largest income loss appeared in quintile 5 (19.6%), followed by quintiles 1 (17.6%) and 4 (17.4%). This is at odds with the simulation results, which show declines of about 12%-13% percent for the bottom 3 quintiles and smaller declines at the top. When including the Auxilio Emergencial as part of household income, households across the income distribution experienced smaller income losses than when excluding this social program. This highlights that the AE program covered households across the income distribution. Income declines, however, were highest for the higher quintiles of the distribution, while there was an income gain for quintile 1, highlighting that the AE program was also more targeted towards the poorest households. Since the microsimulation results did not account for this emergency transfer program (as explained in an earlier section), the results from the 2020 microdata incorporating the AE program cannot be compared with the microsimulations. The rest of the analysis thus focuses on comparing the projected and observed income and poverty changes under the assumption of excluding the AE program.

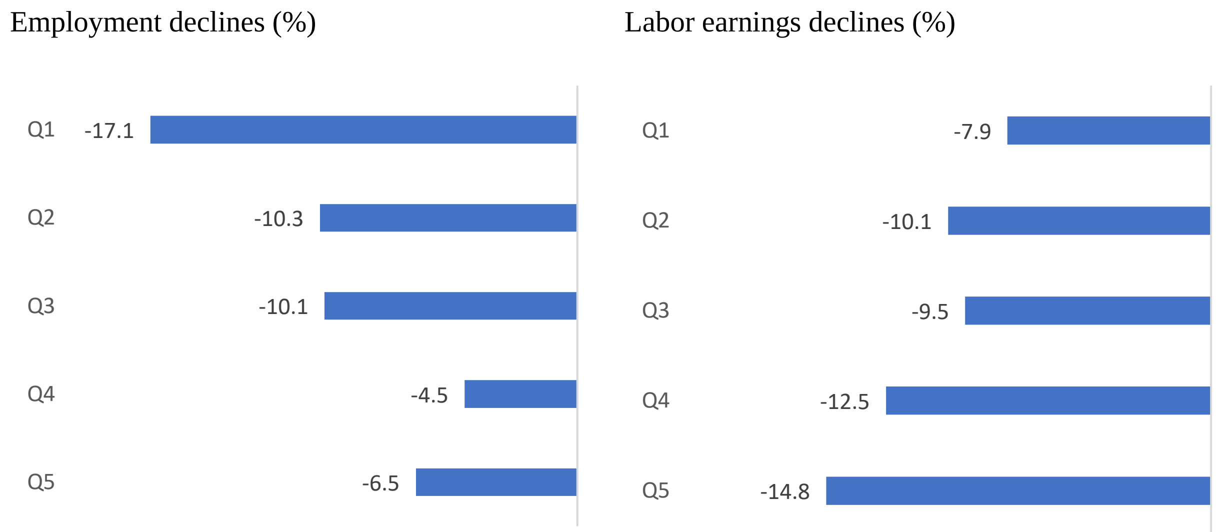
Figure 10. Change in household per capita income between 2019 and 2020. Observed and projected values



Notes: Estimations obtained using the PNAD-Continua 2019 and 2020.

To understand the sources of the difference between the observed change in household per capita income and our projections, we calculate the changes in employment and the changes in labor earnings between 2019 and 2020 using the actual 2019 and 2020 household surveys. Figure 11 shows that quintile 1 suffered the largest decline in employment and quintile 5 faced the largest decline in labor earnings. The decline in employment is captured by the microsimulation model. However, the declines in labor earnings are larger than the loss predicted by the private consumption component of National Accounts.[18] In fact, in 2020 Brazil implemented the Emergency Employment and Income Preservation Program consisting in a reduction of the working day (by 70, 50, or 25 percent) with a proportional reduction in earnings in exchange for employment stability. The evidence is also in line with previous findings that show earnings reductions are an important margin of adjustment strategy during shocks in comparison to employment reductions (Gaurav et al., 2020).

Figure 11. Observed changes in employment and labor earnings between 2019 and 2020



Notes: Estimations obtained using the PNAD-Continua 2019 and 2020.

These results suggest that the macro-micro simulation model requires additional fine-tuning of the assumptions to better take into account labor income losses. For example, protecting employment positions can go hand in hand with a reduction in working hours and a corresponding reduction in labor income that needs to be taken into account. As explained in Section 3.1, workers in some sectors (public administration, utilities, health, and extraterritorial agencies) were protected from any shock in the model. However, the actual data shows that although these jobs were protected, labor incomes did decline in the utilities and health sectors. Similarly, although public sector nominal wages cannot decline, their purchasing power in real terms can. Another assumption that would need to be fine-tuned is the overall private consumption shock applied in the model. When the simulation does not consider the emergency public transfers that governments distributed to households, then the private consumption shock applied in the model needs to be larger. A similar

[18] While the simulation assigns a value of labor earnings equal to zero for workers losing a job, predicts a value of labor earnings for those gaining a job, and adjusts the value for labor incomes for workers who remained in their jobs by the overall change in private consumption per capita, the change in hours of work is not modeled.

consideration applies to changes in other sources of non-labor incomes. In Table 2, we show that, in Brazil, the observed changes in incomes from sources different from the labor market were substantial and varied across the income distribution. For instance, incomes from public transfers grew for all income quintiles and they increased by more for the richest ones who were receiving very little public assistance before the crisis. However, the importance of incomes from public assistance was small for the richest households both before and during the pandemic period. On the contrary, for the poorest quintile this source of income increased its participation in the initial household income from 16% to 39%.

Incomes from other transfers, such as pensions and unemployment insurance, declined for all and the reduction was especially large for the second and fifth quintiles. This source of income represented between 16% and 29% of the initial household income both before and during the pandemic period, indicating that not accounting for this source of income in the analysis could be biasing the microsimulation projections.

Table 2. Observed changes in incomes from sources different from labor between 2019 and 2020

	Other transfers	Public social assistance	Other sources of income
Observed change between 2019 and 2020			
Q1	-8.0%	149.1%	-32.5%
Q2	-23.6%	723.8%	-35.2%
Q3	-2.1%	1422.9%	-34.4%
Q4	-3.8%	2193.4%	-30.7%
Q5	-14.8%	1420.7%	-40.3%
Share of the initial housold income in 2019			
Q1	17.2%	15.6%	4.1%
Q2	24.5%	2.6%	1.9%
Q3	28.9%	0.6%	1.4%
Q4	19.7%	0.2%	1.1%
Q5	18.5%	0.0%	1.0%
Share of the initial housold income in 2020			
Q1	15.8%	38.8%	2.8%
Q2	18.7%	21.0%	1.2%
Q3	28.3%	8.7%	0.9%
Q4	19.0%	4.0%	0.8%
Q5	15.7%	0.5%	0.6%

Source: PNAD-C 2019 and 2020.
Notes: Other transfers include poverty pension, regular pension, unemployment insurance and fishers' insurance. Other sources of income include alimony, donations, allowance, rents, scholarships, and financial gains.

When comparing the observed changes in poverty rates between 2019 and 2020 with our projections, we find that our model correctly predicts an increase in poverty, although the size of the change is smaller than the observed values (Table 3). The poverty rate according to the 2.25 USD-a-day poverty lines increased by 4.9 percentage points and our prediction was 2.7 percentage points. For the 6.85 USD-a-day poverty line, the observed increase was 7.7 while our projection was an increase of 5.2 percentage points. The underestimation of poverty changes is in line with the underestimation of income losses presented in Figure 10.

Table 3. Change in poverty between 2019 and 2020. In percentage points

	US$ 2.25/day	US$ 3.65/day	US$ 6.85/day
Quarter 1	0.82	0.56	0.76
Quarter 2	7.02	8.49	10.81
Quarter 3	6.80	8.52	10.75
Quarter 4	5.06	6.87	8.58
Average	4.92	6.11	7.72
Simulation	2.67	3.99	5.23

Source: PNAD-C 2019 and 2020.

5 Conclusions

In this study we estimated the distributional impacts of the pandemic in five developing countries: Brazil, Sri Lanka, the Philippines, South Africa, and Türkiye. We used a macro-micro simulation approach to capture the impacts of the pandemic via three channels – job loss, labor income declines, and changes in remittances – on total household per capita income/consumption and on the shares of poor, vulnerable, and middle-class populations in each country during 2020.

We analyzed the accuracy of using employment projections based on GDP-employment elasticities for 15 developing countries by comparing the projected employment levels with observed 2020 values. We also validated our microsimulation estimations for Brazil using 2019 and 2020 microdata from the PNAD-Contínua.

Our findings showed, first, that employment estimates for 2020 based on elasticities were reasonably accurate in 11 of the 15 countries. However, in the remaining four countries the projections considerably overestimated employment levels and therefore underestimated job loss due to the crisis. This bias tended to be larger for labor markets that were more disrupted by the pandemic according to the stringency of social distancing measures, changes in workplace mobility, and a measure of scale-up of cash transfer programs. We also projected employment levels using elasticity estimations from a previous recession and found that they generate smaller biases in the projection of employment levels. However, depending on the method used for estimating elasticities, the biases do not differ much from using a non-period crisis.

Second, microsimulations for five countries across different regions of the globe showed declines in the per capita household income or consumption across the entire income/consumption distribution. Overall, the 2020 pandemic resulted in a decline of the middle class and an increase in poverty in all five countries. However, the pattern of impacts across the distribution varied across countries, with no clear pattern. When using employment projections based on elasticities instead of actual employment data, the projected income declines were smaller.

Finally, actual 2020 micro data for Brazil shows that the simulations underestimated the magnitude of the shock throughout the distribution, especially for the wealthy, because they failed to account for the extent of the earnings decline. Consequently, it underestimated the increase in poverty. The evidence shows that during shocks employers or the government may protect employment, but use reduced hours and reduced earnings as the margin of adjustment to the shock, and this needs to be better taken into account in these models. The underestimation of the shock was even larger when using employment projections based on elasticities instead of actual employment data.

This work provides valuable lessons about conducting microsimulations to analyze the distributional impacts of shocks. First, the use of employment projections based on past data could underestimate the magnitude of job losses and, consequently, poverty increases. The use of actual employment data when available is advised to reflect changes in employment levels more precisely.

Second, even when using actual employment data, projections of income changes can be biased if the adjustment mechanisms used during crises are not captured by the model. Adding more complex features to the model, such as the possibility of labor adjustments in the intensive margin, may allow to obtain a better simulation (closer to the real values) of income changes. A similar caveat applies to other sources of income that our model did not capture, such as non-labor incomes different from remittances. In the same line, using a sector-specific scale factor to adjust labor incomes up or down (instead of a single scale factor) could be an improvement. Such data could be obtained from ILO sectoral-specific wage data, although it would only capture earnings of wage employees.

Third, in the context of the COVID-19 crisis, only the agriculture sector was growing in some countries. This allowed us to implement a simplified model where there was no sectoral reallocation. However, in other contexts, where there are substantial job gains in multiple sectors, the model will need to be adjusted to incorporate the possibility that a worker who loses a job in a certain sector gains a job in some other.

References

Adams-Prassl, A., Boneva, T., Rauh, C., and Golin, M. (2020). "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." *Journal of Public Economics,* Volume 189, September 2020, 104245.

Behrens, K., S. Kichko, and J.F. Thisse. "Working From Home: Too Much of a Good Thing." CESifo Working Papers 8831 (2021).

Brum, M., and De Rosa, M. (2021). "Too little but not too late: nowcasting poverty and cash transfers' incidence during COVID-19's crisis." *World Development,* 140(C).

Diop, S., and Asongu, S. (2020). "The Covid-19 Pandemic and the New Poor in Africa: The Straw that Broke." WP No. 20/038, European Xtramile Centre of African Studies.

ECLAC (2020). "Social Panorama of Latin America, 2020." Economic Commission for Latin America and the Caribbean.

Fairlie, R.W., Couch, K, and Xu, H. (2020). "The Impacts of COVID-19 on Minority Unemployment: First Evidence from April 2020 CPS Microdata." Working Paper 27246. National Bureau of Economic Research, Cambridge, MA.

Gaurav, K, Newhouse, D., P. Pacci (2020). "Fewer Jobs or Smaller Paychecks? Labor Market Impacts of the Recent Crisis in Middle-Income Countries." Economic Premise. No. 11. World Bank, Washington, DC.

Gentilini, H., Almenfi, M., Blomquist, J., Dale, P., De la Flor Giuffra, L., Desai, V., Fontenez, M.B., Galicia, G., Lopez, V., Marin, G., Mujica, I.V., Natarajan, H., Newhouse, D., Palacios, R., Quiroz, A.P., Rodriguez Alas, C., Sabharwal, G., and Weber, M. (2021). "Social protection and Job Responses to COVID-19: A Real-Time Review of Country Measures." The World Bank.

Gibss, M., Mengel, F. and Ch. Siemroth. "Work from Home & Productivity: Evidence from Personnel & Analytics Data on IT Professionals." IZA Dicussion Paper 14336 (2021).

ILO (2020). "COVID-19 and the world of work: Impact and policy responses." ILO Monitor 1st Edition. International Labour Organization.

IMF (2021). "World Economic Ourlook. Managing Divergent Recoveries." International Monetary Fund.

Khamis, M., Prinz, D. Newhouse, D., Palacios-Lopez, A., Pape, U. and Weber, M. (2021). "The Early Labor Market Impacts of COVID-19 in Developing Countries: Evidence from High-Frequency Phone Surveys." Policy Research Working Paper No. 9510, World Bank, Washington, DC.

Kugler, M., Viollaz, M., Duque, D., Gaddis, I., Newhouse, D., Palacios-Lopez, A., and Weber, M. (2021). "How Did the COVID-19 Crisis Affect Different Types of Workers in the Developing World?" Policy Research Working Paper 9703, The World Bank.

Lee, S. Y., Park, M. and Shin, Y. (2021). “Hit Harder, Recover Slower? Unequal Employment Effects of the COVID-19 Shock.” NBER Working Paper No. 28354. National Bureau of Economic Research, Cambridge, MA.

Sumner, A., Hoy, C., and Ortiz-Juarez, E. (2020). “Estimates of the Impact of COVID-19 on Global Poverty.” WIDER Working Paper 2020/43, UNU-WIDER.

Vos. R., Martin, W., and Laborde, D. (2020). “How much will global poverty increase because of COVID-19?”. IFPRI Blog.

World Bank (2021). “The Gradual Rise and Rapid Decline of the Middle Class in Latin America and the Caribbean.” LAC Team for Statistical Development Regional Poverty and Inequality Report. Poverty & Equity Global Practice. The World Bank.

Appendix 1. Tables and Figure

Table A1. Month of observed 2020 employment level from National Statistical Offices

Country	Month observed data 2020
ALB	Q1-Q3
BGR	Q3
BRA	Sept-Oct-Nov
COL	November
CRI	Q4
ECU	September
IDN	August
MEX	October
MKD	Q3
PER	September
PHL	October
ROU	Q3
TUR	September
VNM	September
ZAF	Q3

Table A2. Percentage difference between employment level projections for 2020 and actual employment level

Country	Average	Average without outliers	Mean regression	Median regression	Mean regression controlling for GDP	Mean regression controlling for GDP*Informality
ALB	**1.89%**	-5.02%	-4.36%	-3.97%	-4.89%	-5.58%
VNM	**-3.90%**	-4.14%	-4.00%	-3.97%	-3.99%	-4.10%
MKD	-0.48%	**-0.40%**	-0.54%	-0.57%	-0.46%	-0.59%
IDN	0.07%	0.07%	0.07%	0.09%	**0.05%**	-0.38%
TUR	2.04%	0.47%	0.40%	**0.35%**	0.42%	n.a.
BGR	1.32%	0.92%	1.03%	**0.68%**	1.10%	n.a.
ROU	-14.31%	**0.80%**	1.95%	2.26%	1.96%	n.a.
ECU	-3.27%	1.78%	2.17%	2.01%	2.75%	**1.69%**
COL	2.15%	2.90%	2.03%	**2.00%**	2.16%	2.81%
MEX	**3.06%**	3.35%	3.16%	3.26%	3.09%	n.a.
PHL	3.82%	**3.61%**	3.81%	3.68%	3.83%	n.a.
BRA	**5.30%**	6.59%	7.33%	7.39%	7.31%	5.56%
ZAF	**10.39%**	10.73%	10.59%	10.49%	10.59%	20.60%
CRI	16.42%	**15.18%**	15.35%	15.21%	15.52%	18.19%
PER	21.67%	22.98%	23.50%	23.46%	23.51%	**21.57%**

Notes: Cells in grey color highlights the method with the best performance for each country.

Table A3. Projected average per capita household income by initial quintiles

	2019	2020	Diff. 2020-2019
Sri Lanka			
Q1	93.6	91.4	-2.4%
Q2	166.7	162.5	-2.5%
Q3	234.5	228.8	-2.4%
Q4	335.3	328.5	-2.0%
Q5	793.5	780.6	-1.6%
Turkey			
Q1	169.8	167.9	-1.1%
Q2	305.8	304.4	-0.5%
Q3	443.5	441.4	-0.5%
Q4	648.8	646.5	-0.4%
Q5	1,541.8	1,529.9	-0.8%
Philippines			
Q1	1,043.7	998.2	-4.4%
Q2	1,896.7	1,762.9	-7.1%
Q3	2,773.9	2,572.2	-7.3%
Q4	4,162.2	3,867.4	-7.1%
Q5	10,246.0	9,675.2	-5.6%
South Africa			
Q1	16.3	16.0	-1.8%
Q2	66.1	63.5	-3.9%
Q3	127.5	118.1	-7.4%
Q4	293.1	266.5	-9.1%
Q5	1,508.0	1,410.1	-6.5%
Brazil			
Q1	103.6	91.3	-11.9%
Q2	246.4	214.4	-13.0%
Q3	409.1	361.8	-11.6%
Q4	647.7	583.0	-10.0%
Q5	1,925.5	1,756.7	-8.8%

Notes: Projections following the methodology detailed in section 3.1. Income in 2017 PPP USD.

Table A4. Projected poverty, vulnerability and middle-class rates

	2019	2020	Diff. 2020-2019
Sri Lanka			
US$ 2.25/day	3.54	3.91	0.37
US$ 3.65/day	13.19	14.12	0.93
US$ 6.85/day	42.90	44.48	1.58
Vulnerable	35.16	34.37	-0.79
Middle Class	21.30	20.52	-0.78
Turkey			
US$ 2.25/day	0.68	1.11	0.43
US$ 3.65/day	2.65	3.16	0.51
US$ 6.85/day	14.52	15.16	0.65
Vulnerable	29.10	28.90	-0.20
Middle Class	53.50	53.12	-0.38
Philippines			
US$ 2.25/day	4.27	5.58	1.31
US$ 3.65/day	15.50	18.57	3.07
US$ 6.85/day	44.73	49.12	4.38
Vulnerable	31.34	29.31	-2.03
Middle Class	23.27	20.97	-2.30
South Africa			
US$ 2.25/day	29.88	32.70	2.82
US$ 3.65/day	46.51	49.59	3.08
US$ 6.85/day	63.49	65.82	2.33
Vulnerable	13.35	12.45	-0.90
Middle Class	19.76	18.91	-0.85
Brazil			
US$ 2.25/day	5.67	8.35	2.67
US$ 3.65/day	10.70	14.69	3.99
US$ 6.85/day	25.99	31.22	5.23
Vulnerable	24.87	24.54	-0.33
Middle Class	44.63	40.29	-4.33

Notes: Vulnerable defined as a household per capita income between 6.85 and 13 USD a day. Middle class defined as a household per capita income between 13 and 70 USD a day. The last column shows the difference between 2019 and 2020 in percentage points.

Table A5. Projected poverty, vulnerability and middle-class rates using employment elasiticities to obtain 2020 employment level

	2019	2020	Diff. 2020-2019
Turkey			
US$ 2.25/day	0.68	0.81	0.13
US$ 3.65/day	2.65	2.70	0.05
US$ 6.85/day	14.52	14.27	-0.24
Vulnerable	29.10	28.80	-0.30
Middle Class	53.50	54.05	0.55
Philippines			
US$ 2.25/day	4.27	4.84	0.57
US$ 3.65/day	15.52	17.17	1.65
US$ 6.85/day	44.76	47.72	2.96
Vulnerable	31.33	30.23	-1.10
Middle Class	23.26	21.45	-1.81
South Africa			
US$ 2.25/day	29.88	31.45	1.57
US$ 3.65/day	46.51	48.16	1.65
US$ 6.85/day	63.49	65.03	1.54
Vulnerable	13.35	12.76	-0.58
Middle Class	19.76	19.37	-0.39
Brazil			
US$ 2.25/day	5.67	6.33	0.66
US$ 3.65/day	10.70	11.99	1.29
US$ 6.85/day	25.99	27.94	1.95
Vulnerable	24.87	25.10	0.24
Middle Class	44.63	42.71	-1.92

Notes: Vulnerable defined as a household per capita income between 6.85 and 13 USD a day. Middle class defined as a household per capita income between 13 and 70 USD a day. The last column shows the difference between 2019 and 2020 in percentage points.

Figure A1. Percentage difference between 2020 employment projections and actual 2020 employment levels by economic sectors

Notes: The mean regression method controlling for the logarithm of GDP interacted with the informality rate is not available in Bulgaria, Mexico, the Philippines, Romania, and Türkiye. Actual 2020 employments levels by economic sectors come from ILO.