Economics Bulletin

Volume 41, Issue 4

Poverty vulnerability: The role of poverty lines in the post-pandemic era

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Abstract

This paper introduces the results of a novel methodology to estimate country-specific macro-poverty vulnerability. The new poverty vulnerability risk measure considers historical information, statistical significances, poverty lines, and forecasting horizons to proxy exposure to poverty. The application uses aggregated household data and macroeconomic information of 154 countries comprising 97% of the world population. Using the absolute poverty line of US$1.90, a COVID-19 pandemic counterfactual shows that, by 2021, the global expected number of people vulnerable to income impoverishment increased from 205 to 245 million people. Likewise, the poverty level rises from a baseline of 632 to a COVID-19 median counterfactual of 748 million people in 2021. Alternative poverty lines studied in the literature also indicate negative changes in macro-vulnerability performances and poverty levels across 2021–2030.

The authors are thankful to the anonymous referee for the valuable suggestions and comments. Jaime Lara—Universidad de Monterrey (UDEM), Fabian Mendez-Ramos-World Bank. This work started while Fabian was World Bank staff at the Development Research Group (DECRG) and continued while Fabian joined the Model Risk and Governance (MRG), Market and Couterparty Risk Department, Group Chief Risk Officer Vice-Presidency (CROMC), also in the World Bank Group. EDITOR'S NOTE: This manuscript was accepted on September 26, 2021.

Citation: Jaime Lara Lara and Fabian Mendez-Ramos, (2021) "Poverty vulnerability: the role of poverty lines in the post pandemic era", *Economics Bulletin*, Vol. 41 No. 4 pp. 2690-2696.

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Submitted: August 19, 2021 **Published:** December 29, 2021.

1. INTRODUCTION

The literature has discussed the view that income growth constitutes a primary and direct channel to impact poverty (Dollar, Kleineberg, and Kraay 2016). Under this reasoning, recent estimates show that the decrease of GDP caused by the COVID-19 pandemic added between 85 and 115 million people to extreme poverty in 2020 (World Bank 2020). Another channel affecting poverty is the shape of the income distribution. Under parametric assumptions, the form of the income distribution bears an association with an inequality metric (Cowell and Flachaire 2015). Recent literature suggests that income inequality and its changes influenced poverty reduction in recent decades (Bergstrom 2020).

One of the leading United Nations Sustainable Development Goals (SDGs) targets to end extreme poverty by 2030. Before the COVID-19 crisis, some literature highlighted that SDG goal 1 was difficult to achieve (Crespo Cuaresma et al. 2018; Edward and Sumner 2014). In the same direction, this paper aims to show the impact of the COVID-19 crisis on poverty levels predicted to occur by 2030. The research focuses not only on the expected number of poor but also on poverty-vulnerable people. The study considers historical-based shocks of economic growth and changes in income distribution to forecast macro-poverty vulnerability.

2. DATA AND METHODS

Using available information from between 2000 and 2020, we model the growth of mean income in each country following the equation:

$$g_{c,t} = \alpha_c + \underbrace{\theta_c g_t + \delta_c P_t}_{global\,factors} + \varepsilon_{c,t} \ , \tag{1}$$

where the α parameters vary by country, c, and capture the long-run trajectory of the mean income growth. The model accounted for two common factors around all the studied countries: global income per capita growth, g_t, and commodity prices, P_t. These two common factors capture low-frequency country-variation. The evolution of these global factors accounts for the time-varying growth of mean income across all countries. Finally, the fourth component, $\varepsilon_{c,t}$, is a stochastic error factor. Data for country-specific income distribution comes from PovcalNet(2021), and commodity prices come from reports about Commodity Prices Outlook from the World Bank (2021). This study interpolates data in each country when unavailable, as in Mendez Ramos (2019).

To track the variability of the income distribution, we use the absolute Gini coefficient. This absolute measure derives from an identity that involves multiplying the traditional—relative—Gini coefficient by the mean income. The study constructs a vector of means and a matrix of covariances by country using 2000–2019 historical information for global GDP per capita growth, completed with 2019-released predictions for 2020, commodity prices, stochastic error terms derived from (1), and absolute Gini coefficient growth rates. Then, assuming a multivariate normal distribution, the next step produces for these four variables—country-specific and time-independent—randomly drawn simulations.

Predicted mean income growth by country is recovered using the Monte Carlo simulation results and the OLS estimates of parameters α, θ_c, and δ_c from equation (1). Additionally, we predict the relative Gini coefficient, G_t, as a residual from the simulation outcomes of mean income, $\mu_{Y_{c,t}}$, and the absolute Gini coefficient, $A_{c,t}$, i.e., $G_t \equiv A_{c,t}/\mu_{Y_{c,t}}$. A reasonable assumption at a country level is to presume that income obeys a lognormal distribution (Bergstrom 2020; Lopez and Serven 2006). Thus, two parameters, such as the relative Gini coefficient and the mean income, are needed to depict country-specific income distributions fairly.

Recursively, we construct randomly simulated mean income and relative inequality trajectories indexed from 1 to 5,000 before recovering the share of the population living below a fixed poverty line using the World Population Prospects population forecasts (United Nations 2019). Our findings are based on four absolute poverty lines: \$1.90, \$3.20, \$5.50 and \$15 (USD per day in 2011 PPP terms), and a recently introduced societal poverty line, $SPL = \{US\$1.90\,, US\$(1 + 0.5\ \times median)\}$, where *median* represents the daily median level of income or consumption per capita in the household survey. In principle, the societal poverty line attempts to account for the absolute and relative natures of poverty (Jolliffe and Prydz 2021; World Bank 2020). The next step involves recovering aggregated poverty measures at regional and global levels.

Finally, the paper introduces a novel measure to emphasize poverty vulnerability from a macroeconomic perspective. Our macro-poverty vulnerability measure differs from other vulnerability metrics. In contrast with Dang and Lanjouw (2017) and López-Calva and Ortiz-Juarez (2014), who used within-country and household-specific shocks, our vulnerability metric is extracted from country-specific aggregated shocks and global macroeconomic disturbances. The ex-ante metric is based on recovered uncertainty derived from historical information.

Our results of poverty vulnerability denote the difference between an α_s (99.5) percentile and the expected mean of the forecasted poverty distribution at a specific horizon, $\mathbb{E}(N_{z,T})$. In specific, the macro-poverty vulnerability is defined as $PV_{\alpha_s,z,T} \equiv VaR_{\alpha_s,T}(N_{z,T}) - \mathbb{E}(N_{z,T})$, where $VaR_{\alpha_s,T}(\cdot)$ proxies a worst-case scenario of the number of people living below a specific poverty line, z, time horizon, T, with an α_s% confidence, i.e., $VaR_{\alpha_s,T}(n_{z,T}) = \inf\{n_{z,T} \in \mathbb{R}^+ : P(N_{z,T} \leq n_{z,T}) > 1 - \alpha_s\} = F^{-1}_{N_{z,T}}(1 - \alpha_s)$. Thus, $PV_{\alpha_s,z,T}$ is an approximation of unexpected poverty.

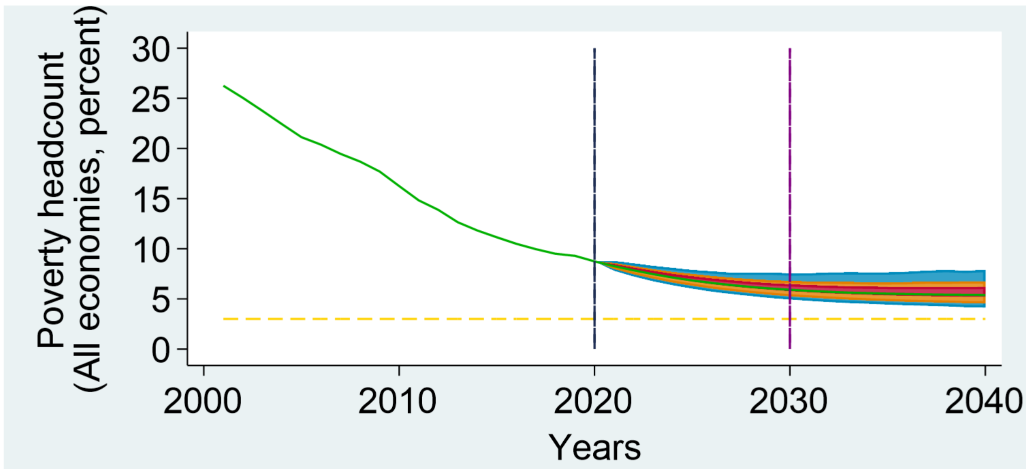
3. Results

Our forecasted poverty benchmark—baseline—results are built on 2000–2020 data, completed with 2019–2020 growth predictions of GDP per capita from the International Monetary Fund (IMF) and released in October 2019 (IMF, 2019). Note that the IMF predictions of growth of GDP per capita for 2020 elicited in April 2021 (IMF, 2021) ascertain the impact of COVID-19 on poverty levels and vulnerability. The baseline and COVID-19 counterfactual account for 2020 commodity prices and assume that the 2020 relative Gini coefficients behave in the same form as they did in 2019. Then, both the baseline and COVID-19 poverty estimates rely on random simulated trajectories beginning in 2021.

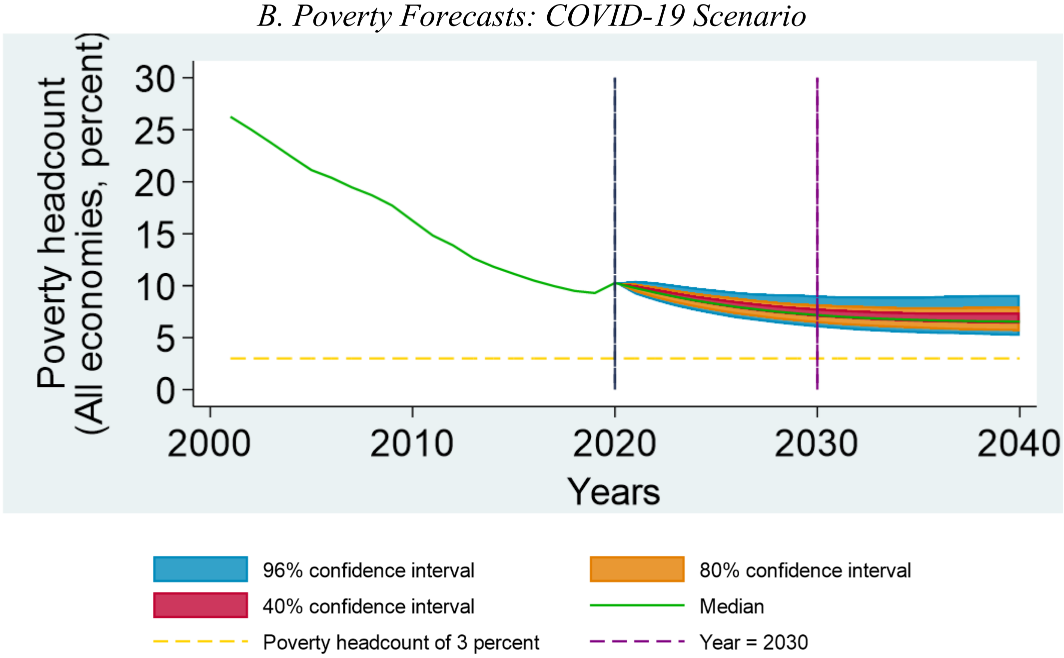
Figure 1 shows the simulated trajectories of global poverty using the US\$1.90 line and three confidence intervals. Panel A establishes the baseline. The counterfactual shown in Panel B considers the average income effect of the COVID-19 crisis in 2020, illustrating a jump in poverty in 2020. In Table 1, with the baseline, our model predicts 632 million people in extreme poverty by 2021 and 489 million by 2030. The COVID-19 scenario estimates poverty headcount by 2021 as 116 million people larger than the results in the baseline. The 2021 COVID-19-driven increase in poverty is sustained across time horizons; our median predictions show an increment of 106 million extreme poor by 2030, making the United Nations SDG Goal 1 more challenging to achieve.

Figure 1. Global Extreme Poverty and the COVID-19 Crisis

A. Poverty Forecasts: 2000–2020 Baseline



B. Poverty Forecasts: COVID-19 Scenario



Notes: The results are based on the US$1.90 a day poverty line in constant 2011 PPP. Global aggregated poverty headcount statistics are derived from 5,000 country-specific random simulations by year from 2021 to 2040. Panel A: By 2021 and 2030, the expected poverty headcount is 8.3% and 5.9%, with a standard deviation of 0.24% and 0.63%, respectively. Panel B: By 2021 and 2030, the expected poverty headcount is 9.8% and 7.3%, with a standard deviation of 0.32% and 0.73%, respectively.

Between 2021 and 2030, COVID-19 is predicted to have a permanent harmful effect on poverty. This detrimental effect is sustained across different poverty lines and horizons (Table 1). Compared to the baseline, the most significant absolute change in poverty is observed using the US$5.50 line, where the COVID-19 scenario increased poverty levels by 264 and 386 million people by 2021 and 2030, respectively. In the baseline vs COVID-19 comparison, the lowest absolute increase occurs in the societal poverty line: 88 and 111 million people difference by 2021 and 2030, respectively.

Table 1. Global Poverty and Macro-Poverty Vulnerability Pre- And Post-COVID-19

Poverty Lines:	US$1.90	US$3.20	US$5.50	US$15	SPL
		2000–2020 Baseline			
2021 Headcount (million)	632	1,473	2,840	5,387	2,099
2030 Headcount (million)	489	1,080	2,242	5,157	2,039
2021 Vulnerable (million)	205	284	293	185	220
2030 Vulnerable (million)	847	1,080	1,164	792	835
		COVID-19 Scenario			
2021 Headcount (million)	748	1,689	3,104	5,544	2,187
2030 Headcount (million)	595	1,303	2,628	5,453	2,150
2021 Vulnerable (million)	245	332	331	193	234
2030 Vulnerable (million)	954	1,228	1,308	810	882

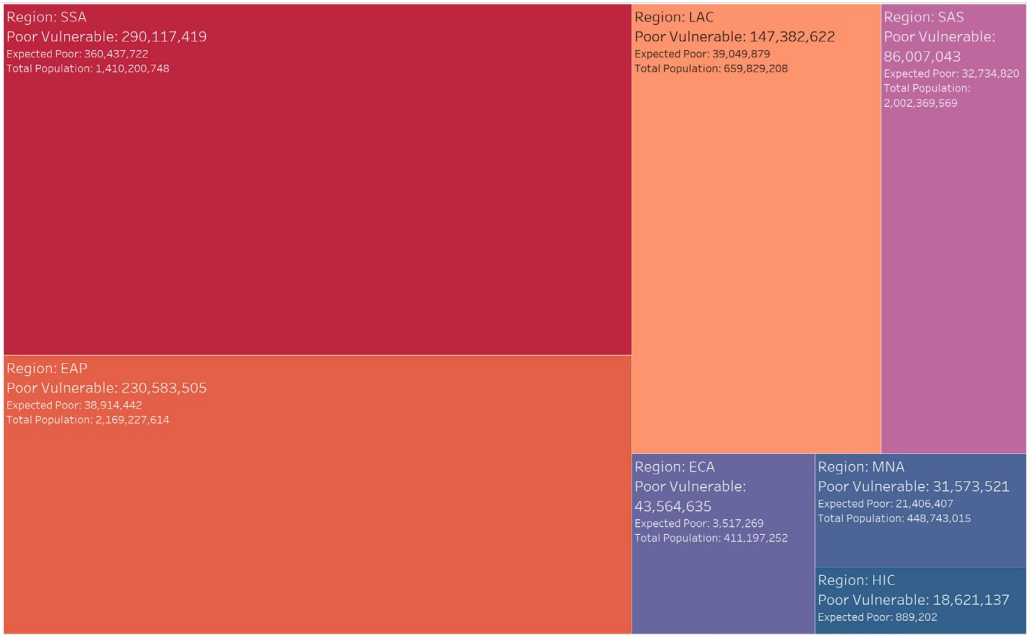
Notes: SPL stands for Societal Poverty Line. Baseline and COVID-19 estimates use IMF GDP per capita growth rates reported in October 2019 and April 2021, respectively (IMF, 2021, 2019). The reported poverty headcount numbers are median estimates. The results are derived from 5,000 country-specific random draws per year. The reported vulnerability measure is defined as the 99.5 percentile minus the expected value of the predicted poverty headcount by a specific horizon: 2021 or 2030.

Macro-poverty vulnerability estimates also indicate notable effects of the COVID-19 crisis (Table 1). The difference in the US$1.90 and US$3.20 results between the baseline and COVID-19 counterfactual shows that the pandemic negatively affected levels of macro-poverty vulnerability; the COVID-19 pandemic augmented the number of vulnerable individuals by 40 and 48 million people by 2021, respectively. By 2030, the most significant absolute increase in macro-poverty vulnerability—in the baseline vs COVID-19 comparison—appears in the results of the US$3.20 and US$5.50 poverty lines. On the contrary, in 2021 and 2030, the US$15 and SPL poverty lines—despite their high absolute poverty headcount numbers—show modest changes of macro-poverty vulnerability driven by the effects of COVID-19; these subtle changes are comparable to—and even smaller than—the US$1.90 outcomes in 2021 and 2030.

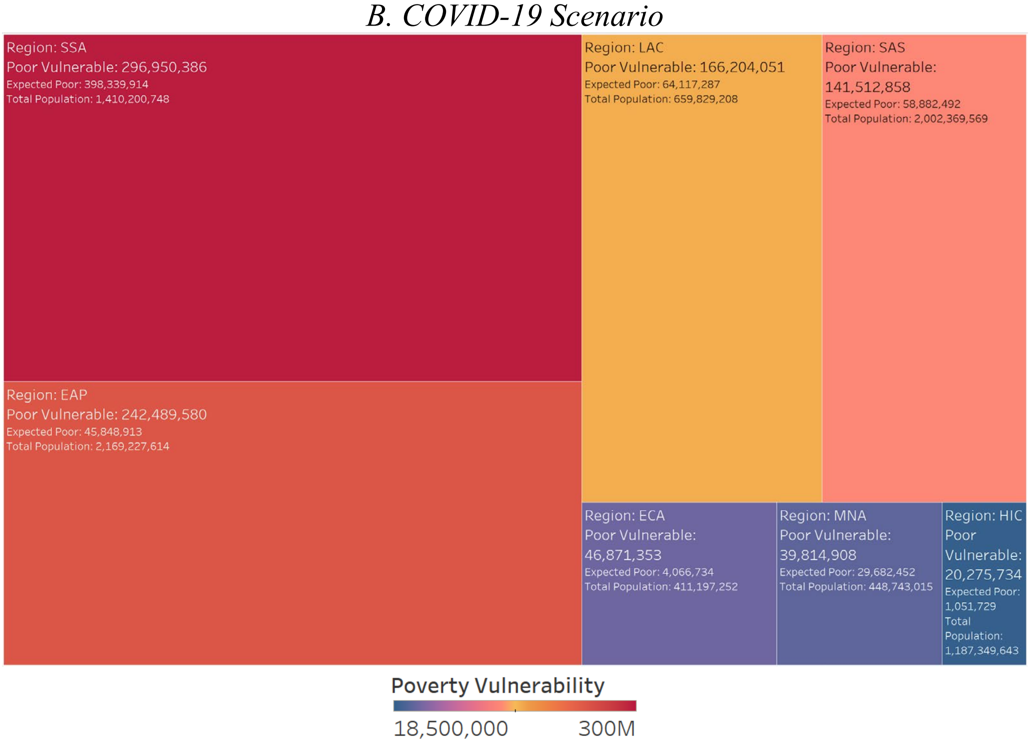
Sub-Saharan Africa (SSA) and East Asia and the Pacific (EAP) account for half of the global poverty vulnerability. Figure 2 shows the regional distribution of the vulnerable population by 2030 using the US$1.90 poverty line for the baseline and the COVID-19 counterfactual. Besides, Latin America and the Caribbean (LAC) and South Asia (SAS) are the two regions heavily impacted by the COVID-19 crisis, with a significant increase in predicted extreme poor-vulnerable populations in 2030: 19 and 56 million, respectively. The increase in the number of vulnerable people to extreme poverty is particularly relevant in LAC countries, where the share of the population under risk is the highest of all regions: 22 and 25 percent in the baseline and COVID-19 counterfactual.

Figure 2. 2030 Global Poverty Vulnerability: Dimensions by Developing Regions

A. 2000–2020 Baseline



B. COVID-19 Scenario



Notes: The results are based on the US$1.90 a day poverty line in constant 2011 PPP. HIC stands for high-income countries. Developing regional names: ECA stands for Europe and Central Asia, MNA denotes the Middle East and North Africa, SAS represents South Asia, LAC represents Latin America and the Caribbean, EAP stands for East Asia and the Pacific, and SSA denotes Sub-Saharan Africa.

4. CONCLUSIONS

The COVID-19 pandemic has increased expected poverty across absolute and societal poverty lines. The introduced macro-poverty vulnerability risk measure also indicates an increase in the number of people highly exposed to face income deterioration in the following years. These macro-poverty vulnerability outcomes are uneven across countries and regions and highlight the requirement for heterogenous policies to hedge against country-specific shocks and global macroeconomic disturbances.

This study works because of the aggregate nature of the analysis covering a high proportion of the world population with a minimal requirement of country-specific information. However, there are limitations in interpreting outcomes at country-specific and regional levels, and additional nuanced analysis is suggested. Our contribution to the literature is at the intersection of health and income poverty using a high-level macroeconomic model. The study is limited to the macroeconomic domain, leaving aside the microeconomic analysis of the effects of COVID-19 for additional research.

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