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Uncertainty in Ex-Ante Poverty and Income Distribution

Insights from Output Growth and Natural Resource Country Typologies

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Abstract

This paper studies future poverty, inequality, and shared prosperity outcomes using a panel data set with 150 countries over 1980–2014. The findings suggest that global extreme poverty will decrease in absolute and relative terms in the period 2015–2030. However, absolute poverty is likely to increase by 2030 in resource-output oriented countries and economies with low rates of output per capita growth. Countries with high growth rates of output are expected to achieve poverty levels below 3 percent by 2030. Global and country aggregations show a decrease in income inequality by 2030; though, significant downside risks could increase wealth inequality in high- and low-output growth economies by 2030. Substantial uncertainty, as measured by the variability of the simulated outcomes, exists on shared prosperity gaps across the studied country typologies.

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Uncertainty in Ex-Ante Poverty and Income Distribution

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I. INTRODUCTION

This paper follows a strand of the literature that debates that sustained economic growth is the primary source of poverty alleviation (World Bank 2016, and World Bank; International Monetary Fund 2016, and World Bank 2018). In addition, this research focuses on potential future pathways in wealth inequality based on the idea that, in multiple countries, economic growth has played a vital role in the lower end of the income distribution diminishing poverty rates (Dollar, Kleineberg, and Kraay 2016) and in increasing wealth at the higher end—especially for the very rich—(Campos-Vazquez, Chavez, and Esquivel 2017). Also, our study aims to highlight the recent historical role of both the natural resource sector and the speed of economic growth to predict future changes in poverty and income distribution.

The contribution of this paper to the literature on poverty and income distribution is threefold. First, our Monte Carlo simulation procedure offers an alternative method of estimating the dynamics of the income distribution in a simple setup, expanding the work of World Bank (2014) by modeling of the randomness of the growth rate of the Gini coefficient and its interaction with mean income growth. At the country level, the simulations assume independent movements of the growth rates of both average income and inequality according to historical and country category benchmarks. The second contribution of this paper is that it provides estimates of the certainty of future poverty and some aspects of the income distribution by 2030 for some country categories. The standard deviation of the Monte Carlo simulated projections accounts for the uncertainty of the poverty headcount, inequality and shared prosperity measures. The third contribution of this study intersects the discussion on the position of natural resource-rich countries regarding their effects on long-term growth (Havranek, Horvath, and Zeynalov 2016) versus the position of more-diversified economies, and the significant role that the speed of economic growth across countries plays in poverty alleviation (Ravallion 2013), income inequality (Ravallion 2018), and changes in shared prosperity measures (Dollar, Kleineberg, and Kraay 2014).

Uncertainty in poverty projections is a topic that has been long debated in the literature. In many cases, researchers study the uncertainty of ex-ante poverty outcomes via scenario analysis. For instance, Ravallion (2013) finds that alternative scenarios could lead to very different poverty reduction outcomes. A "pessimistic" scenario could see 1,000 million people lifted out of poverty

over the period 2012–2062, while a more "optimistic" state could achieve the same results but in a period ending between 2025 and 2030. Lakner, Negre, and Prydz (2014) acknowledge uncertainty in the speed of change for different percentiles of the income distribution. These authors use scenario analysis to test how meaningful the difference of growth rates between the income growth of the bottom 40 percent (B40) and the mean of the income distribution is for future world poverty attainment. Chapter 4 of World Bank (2014) simulates potential outcomes for income growth and its effects on the poverty headcount under a variety of economic growth contexts and distributional considerations highlighting significant uncertainty in future income poverty attainments. More recently, World Bank (2018) discusses poverty projections up to 2030 and tests its premises—of country future growth rates and the nature of this growth—to stress that there is some degree of uncertainty in poverty outcome attainments.

Our paper approximates growth rates in the mean income and the Gini coefficient by combining household—income and expenditure—survey data from 1980 to 2015 with macroeconomic information from 1970 to 2015 and using country typologies. The country classifications denote different sets of interconnected features—institutions—related to production methods, such as government and political systems, regulation, human capital formation, trade structure, and innovation, among others. In this paper, two embedded institutional characteristics—resource-output orientation and GDP per capita growth information—are exploited to derive future poverty and income distribution outcomes by country and country aggregations. Despite the arbitrary selection of the country typologies, these classifications aim to show that there is heterogeneity in poverty and income distribution changes beyond global aggregated outcomes. Our selected country typologies are two among several others that could be used to understand the commonalities of environments in which firms operate. However, to our knowledge, no other study considers these two specific types of country categorizations to explain future movements in poverty rates, inequality, or shared prosperity measures.

We denote resource-output and non-resource-output oriented economies as ROC and NROC, respectively.[2] While natural resource-related activities present opportunities for economic growth and poverty reduction, they also involve risks such as commodity-export dependency and

[2] Throughout this paper, we use ROC economies, ROC countries, or simply ROCs interchangeably. The same rule applies for NROC economies.

reduced economic diversification. There is a segment of researchers that argue that countries with oil or another type of natural resource wealth have failed to grow more rapidly than those without, denoting this phenomenon as the natural resource curse (Frankel 2010). On the contrary, some literature debates that resource-rich countries face a curse of concentration—of export revenues—rather than a curse of natural resource abundance per se (Lederman and Maloney 2007, and Lederman and Maloney 2012). Research also shows that natural resource countries are also more prone to have lower quality institutions, suffer from deindustrialization and have a higher likelihood of civil war, Dutch disease and macroeconomic volatility (van der Ploeg 2011).

Some of the literature claims that there is an adverse association between macroeconomic volatility and economic growth across countries. Hnatkovska and Loayza (2003) identify the adverse causality effect from volatility to growth, which is notably worse in poor and institutionally underdeveloped countries and in economies that are unable to put countercyclical fiscal policies into practice. van der Ploeg (2011) asserts that the volatility of resource windfalls hurts economic growth, especially in countries with less advanced systems and institutions. In this regard, periods that involve high commodity prices of natural resources could likely lead to an increase in productive activities in countries with good institutions, whereas economies with weak institutions might devote more resources to rent-seeking behaviors (Bulte and Damania 2008, and Crafts and O'Rourke 2014).

Based on concerns related to the downside risks associated with the volatility of resource rents and output and considering our predictions of the poverty headcount, resource-based countries might continue reforms that strengthen their institutions, including those that involve risk management procedures that hedge for more stable economic performances. These institutions could foster the study and implementation of fiscal—probably countercyclical—rules (Devarajan, Dissou, Go, and Robinson 2015, and Galego Mendes and Pennings 2017), commodity price hedging strategies (Frankel 2017), diversification strategies for the economy (Lederman and Maloney 2012), and other actions. Also, economies could design plans and policies that would provide confidence, stability, and more transparent use of resource rents.

We denote low-, medium-, and high-output growth countries with LOGC, MOGC, and HOGC, respectively, using GDP per capita growth over the period 1970–2014.[3] The identification of economies via the growth rate of output per capita over a recent 45-year period aims at capturing similar macroeconomic performance as well as understanding the implications for future changes in poverty and the income distribution. For instance, the average high-output growth observed in some countries could help us identify institutional arrangements that may be valuable for poverty alleviation or vice versa; low-output growth country characteristics suggest some poor practices implemented in corporate and governmental structures.

In 2013, the World Bank set two main goals to guide its work: end extreme poverty by 2030 and boost shared prosperity. These two goals were aligned to support the Millennium Development Goals (MDGs), which were the predecessors of the current Sustainable Development Goals (SDGs) established by the United Nations (Cruz, Foster, Quillin, and Schellekens 2015). The World Bank's twin goals specifically target reducing extreme poverty in the world to less than 3 percent by 2030 and promoting income growth for the bottom 40 percent of the population in each country (World Bank 2014). In this context, one of our main results indicates that alleviating extreme poverty below the 3 percent target across the world economies by 2030 is an outcome with a very low probability—below two percent in all our simulations.

Our results suggest that depending on the historical growth rates used in the projection exercises, world poverty outcomes in 2030 could vary over a broad range. For instance, our more positive result of poverty headcount at the global level indicates a median value of 4.6 percent with a standard deviation of 0.48, whereas the more pessimistic result shows a median outcome of 8.9 percent with a 0.93 standard deviation.[4] Our 2030 world predictions confirm the results of World Bank (2014)[5] and World Bank (2018), indicating that recent historical country performances in terms of income growth and changes in income inequality and commodity prices are insufficient to reach a poverty headcount below 3 percent. World Bank (2014) suggests that countries will have to depart from their historical experiences in terms of both economic growth and distributional effects and policies to reduce poverty faster and achieve the 2030 target. This

[3] In this paper we interchangeably use LOGC economies, LOGC countries, or simply LOGCs. The same rule applies for MOGC and HOGC economies.
[4] The 4.6 and 8.9 poverty rate estimates imply that approximately 370 million and 720 million people live in extreme poverty conditions—subsisting with less than $1.90 purchase power parity (PPP) 2011 U.S. dollars per day—by 2030.
[5] Note that World Bank (2014) uses a poverty line of $1.25 PPP 2005 PPP U.S. dollars per day.

statement aligns with the discussion in World Bank (2018), which adds that the world's poorest countries must grow at a rate that surpasses their historical episodes to reach the 3 percent target.

Besides, our aggregated results indicate that global income inequality will most likely decrease between 0.7 and 1.9 Gini points (on the Gini scale of 0-100) in the period 2015–2030.[6] From this perspective, these results are conservative but follow a decrease that is similar to that in the latest historical patterns, as discussed in Anand and Segal (2015), Lakner and Milanovic (2016), and World Bank (2016). Our results on the reduction in global inequality by 2030 also appear to be in the same direction as those predicted in Hellebrandt and Mauro (2015), where an average decline in the Gini coefficient of global inequality is estimated with a magnitude of 4 Gini points in the period 2013–2035. Our estimates of the global Gini coefficient show substantial uncertainty and downside risks that involve outcomes that imply an increase in the level of inequality in the 2015–2030 period.

Our simulation outcomes also show that NROCs—or more-diversified economies—and countries with fast annual output growth rates are likely to reduce extreme poverty to below 3 percent by 2030. In contrast, the results for income inequality in these more-diversified economies and high-output growth countries involve substantial uncertainty. These estimates predict substantial downside risks in pushing for increasing inequality over the period 2015–2030 in these countries, especially in HOGCs. The results also indicate that ROCs and LOGCs are quite likely to observe a decline in relative extreme poverty and income inequality across the period 2015–2030; they are, however, facing downside risks associated with increasing extreme poverty in absolute terms. MOGCs are the only economies that show positive results in terms of poverty and inequality attainments: declining relative and absolute poverty paths and diminishing income inequality by 2030.

Furthermore, the results regarding the shared prosperity gaps show considerable heterogeneity between and within country classifications in the period 2015–2030. Measured by the standard deviations of simulated outcomes, all the results indicate that there is significant uncertainty in shared prosperity gaps; HOGCs and LOGCs show higher levels of variability. The overall results highlight the importance of fostering economic growth; however, they underline the

[6] Our estimates are population-weighted averages of country Gini coefficients.

relevance of designing effective social spending and fairer taxation mechanisms to tackle potential increasing income inequality.[7,8]

The rest of the paper is organized as follows. Section II describes the modeling details and the assumptions used to predict poverty rates, inequality, and shared prosperity measures. Section III discusses the exact definitions and few features of the country typologies. We discuss data and descriptive statistics by country typologies in section IV. Section V outlines our simulation procedure whereas Section VI summarizes the predicted results. Finally, we make some concluding observations in Section VII.

II. MODEL

The selection of the functional form of the income distribution is essential for constructing reliable projections. Note that the parameterization of the distribution of income could take a variety of well-studied functional forms (Chotikapanich 2008, and Cowell and Flachaire 2015). The shape of the distribution of income could have implications regarding the flexibility that is needed to accommodate the dynamics of the projected parameters. For instance, in general, a three-or four-parameter distribution is preferred and has more flexibility to incorporate the characteristics of skewness or the tails of the income distribution than one that considers only two parameters. Despite the large variety of functional forms, the most critical binding constraints for selecting the best parametric distribution to fit income are the availability and consistency of the sample statistics.[9]

In addition to the difficulty of choosing the functional form of the income distribution, there are other potential concerns when projecting income, such as modeling and data measurement errors. For instance, if we use an econometric model to predict changes in the mean or specific percentiles of the income distribution, our modeling errors could be related to the correct specification, omitted variable bias, and reverse causality. Besides, data measurement

[7] van der Weide and Milanovic (2018) empirically show that high levels in inequality reduce income growth among the poor but increase the income growth of the rich.

[8] The trends of our simulated outcomes remain consistent when using various sample periods, country typology threshold definitions, and substituting the growth rates of per capita consumption with GDP per capita to proxy missing household mean income observations.

[9] For instance, Ravallion (2015) highlights that the literature has identified three relevant parameters that depict income growth: inequality, poverty, and the size of the middle class. This type of information is, however, not available in some countries or across several time periods.

errors, caused by either sampling or non-sampling issues, are a problem that could arise when projecting future income growth. Given that income statistics and poverty measures depend on Census and household survey data, mistakes made when collecting this information might skew the recovered statistics, for example, Gini coefficients and income averages.

Another significant concern to model the dynamics of the income distribution is related to the causality between inequality and economic growth. When we think about the forces interacting between wealth inequality and economic growth, we might be hesitant to make conclusions regarding the magnitudes and even directions. In the specific case of wealth inequality affecting growth, there is a strand of the economic literature highlighting that inequality is suitable for incentives and therefore for growth in market-oriented economies, whereas another strand argues that inequality has a direct adverse effect on economic growth (Aghion, Caroli, and Garcia-Penalosa 1999).[10]

Recent empirical research finds that the presence of weak instruments, using a system generalized method of moments (GMM) procedure, is in detriment of robust conclusions about the effect of inequality on growth in either direction (Kraay 2015). Likewise, by making use of robust GMM estimations, Ferreira, Lakner, Lugo, and Özler (2018) find no significant result of total income inequality affecting economic growth. Lastly, Marrero and Serven (2018) develop a model where the impact of inequality on growth can be positive or negative, as it combines two types of effects—indirect and direct—that could be mutually opposing. Poverty is used to identify the indirect impact of inequality on growth. The effect of inequality on the aggregate investment of non-poor individuals can explain the direct outcome. The authors find that the sign and immediate impact of inequality on growth are fragile; this impact can take a positive or negative sign depending on the specific model used and the econometric approach employed. The authors also find that the indirect effect of inequality and growth—via poverty—is negative and significant at high—but not extremely high—poverty rates, whereas it is nonsignificant at low poverty rates.

[10] Aghion, Caroli, and Garcia-Penalosa (1999) discuss that there are at least three reasons why inequality might have a direct adverse impact on growth in economies with heterogeneous wealth or human capital endowments and imperfect capital markets: i) inequality reduces investment opportunities; ii) inequality deteriorates borrowers' incentives; and iii) inequality generates macroeconomic volatility. In contrast, the same authors discuss three views of why inequality can be growth-enhancing: i) Kaldor's hypothesis that the marginal propensity of the rich to save is higher than that of the poor; ii) investment indivisibilities for setting new industries: in the absence of a broad and well-functioning market for shares, wealth needs to be sufficiently concentrated to be able to cover large sunk costs; and iii) incentive and moral hazard considerations: the trade-off between output efficiency and (wage) equality.

The following subsections describe the processes behind the estimation of future poverty, inequality, and shared prosperity measures. Subsection A explains our assumptions regarding the income distribution and the details of the econometric method used to project income growth. Subsection B provides a detailed description of our assumptions to model the Gini coefficient dynamics. We present our definitions of relative income inequality and shared prosperity gaps in Subsection C.

A. Income Distribution and Mean Income Growth

In this study, $Y_{c,t}$ denotes the income of the population in country c at period t. The income variable $Y_{c,t}$ is transformed via natural logarithms, such that $w_{c,t} \equiv \ln Y_{c,t}$. A conservative and common assumption is to consider that $w_{c,t}$ is distributed as a normal random variable $N\left(\mu_{w_{c,t}}, \sigma^2_{w_{c,t}}\right)$. The previous consideration implies that the income of the people in country c at period t should follow a lognormal probability distribution function, such as $Y_{c,t} \sim \log N\left(\mu_{w_{c,t}}, \sigma^2_{w_{c,t}}\right)$.[11,12]

To provide the dynamic framework for the income distribution, we focus on modeling the mean and variance parameters of the lognormal assumption. Then, we construct a model that predicts the growth of both the mean income and the Gini coefficient.[13] The combination of independent randomly generated patterns of average income growth and changes in inequality allows us to quantify the uncertainty associated with the overall change in the income distribution.

Growth in the mean of the income distribution is assumed to follow a basic linear econometric specification where global and idiosyncratic factors play a role. Growth in the real mean income in country c, g_c, [14,15] follows the stochastic pattern shown in Equation (1). This stochastic process consists of four components, three of which involve random elements. The first component is an idiosyncratic fixed effect factor, α_c, which measures the long-run trajectory of

[11] Cowell and Flachaire (2015) discuss that the lognormal distribution is useful to fit few economic processes. These authors note that there are important theoretical weaknesses in a process that involves adjusting the upper tails of more broadly-based income distributions.
[12] Lopez and Servén (2006) provide empirical evidence indicating that income can be effectively proxied by a lognormal distribution.
[13] As mentioned in the introduction, our dynamic framework expands on World Bank (2014).
[14] Both income and expenditure household survey information were retrieved from World Bank (2019). Consumption and GDP data were retrieved from PWT 9.0 (Feenstra, Robert Inklaar, and Marcel P. Timmer 2015).
[15] If household survey's information of mean income or mean expenditure is not reported in a specific period, the missing observations are inputed using the growth rates of per capita consumption or GDP per capita.

the mean income growth for country $c \in C_h$, such that C_h is a subset of the complete set of countries in the world, C . The subindex h is used to denote country groups or typologies. In this paper, six country groups are utilized such that $h \in H$ = { all, NROCs, ROCs, HOGCs, MOGCs, LOGCs }.[16] The second component in Equation (1) is a factor affecting global income per capita growth, $\theta_c g_t$; this is a semi-stochastic compound factor consisting of a country-specific parameter, θ_c, which weights the response of country c to shocks in global income per capita growth, g_t. The third component is also a global and semi-stochastic compound factor, $\delta_c p_t$; this component consists of one country-specific parameter, δ_c, and one random variable that accounts for global real commodity prices, p_t. Finally, the fourth component, $\varepsilon_{c,t}$, is an idiosyncratic stochastic error factor.

$$g_{c,t} = \alpha_c + \underbrace{\theta_c g_t + \delta_c p_t}_{global\ factors} + \varepsilon_{c,t} \ , \qquad \text{for all } c \in C_h \ , \tag{1}$$

where the expected value of the error term in Equation (1) is assumed to be zero, $\mathbb{E}\left[\varepsilon_{c,t}\right] = 0$, for all countries c and periods t. The expected values of global income per capita growth and real commodity prices are assumed to be constant and can be proxied by their sample means, $\mathbb{E}[g_t] \equiv \mu_g$ and $\mathbb{E}[p_t] \equiv \mu_p$, respectively. In addition, the variance of the idiosyncratic error term in Equation (1) is assumed to follow a homoscedastic process: $var\left[\varepsilon_{c,t}\right] = \sigma^2_{\varepsilon_c}$, for all t. The same assumption is made for the variance statistics of the global factors in Equation (1). Homoscedastic processes are attached to global income per capita growth and real commodity prices; both are respectively proxied by their sample variances: $var[g_t] = \sigma^2_g$ and $var[p_t] = \sigma^2_p$, for all t.

Furthermore, the covariance between the idiosyncratic error term and the global factors is assumed to be null, which implies that $\mathbb{E}\left[\varepsilon_{c,t} g_t\right] = 0$ and $\mathbb{E}\left[\varepsilon_{c,t} p_t\right] = 0$, for any country c in period t. Finally, the global factors g_t and p_t are associated, however, we assume that this concurrent association is almost zero, implying a contemporaneous covariance stationary process: $cov[g_t, p_t]$

[16] Table 1 provides the definitions of the country groups in H.

$= \gamma_{g,p}(0) \approx 0$, for all t.[17] Under the above discussed assumptions, we can estimate Equation (1) country by country using OLS (Wooldridge 2001).[18]

In addition to the above-stated econometric and statistical considerations, the coming up parametric distributions are assumed to complete the description of the random components affecting mean income growth at the country level:

$$\varepsilon_{c,t} \sim N\left(0, \sigma_{\varepsilon_c}^2\right). \tag{2}$$

$$g_t \sim N\left(\mu_g, \sigma_g^2\right). \tag{3}$$

$$p_t \sim TN\left(\mu_p, \sigma_p^2, a, b\right), \text{ s.t., } a = 0, \quad b = \infty^+ , \tag{4}$$

where, $N(\cdot)$ denotes a normal distribution and $TN(\cdot)$ represents a univariate truncated normal distribution with mean μ_p, variance σ_p^2, and lower and upper bounds a, and b, respectively.

B. Dynamics of Relative Inequality

We assume that the logarithm of the Gini coefficient, $\ln G_{c,h,t}$, follows a random walk process limited by—recent historical—Gini index thresholds. Thus, the exponential growth rate of the Gini coefficient, $g_{G_{c,h,t}}$, is assumed to follow a random normal behavior bounded by thresholds of historical Gini coefficient levels. Equations (5) and (6) summarize these assumptions. In this regard, the thresholds of the Gini coefficient play a conservative modeling role; these boundaries indicate that countries are not able to attain inequality levels beyond those observed in recent history.[19]

[17] Under these econometric considerations, the expected variance of income growth for all periods t can be estimated by $var\left[g_{c,t}\right] \equiv \sigma_{g_{c,t}}^2 \approx \theta_c^2 var[g_t] + \delta_c^2 var[p_t] + var\left[\varepsilon_{c,t}\right] + 2\theta_c \delta_c cov[g_t, p_t]$.

[18] Under the explained assumptions, this panel data structure represents a seemingly unrelated regression (SUR) model. Wooldridge (2001) highlights that when the SUR model does not place cross equation restrictions on the coefficients, the separated OLS estimation of Equation (1)—country to country—corresponds to using the system OLS estimator.

[19] In the most conservative case, the neutral income distribution assumption could be implemented by holding the Gini coefficient constant across the simulated periods: $g_{G_{c,h,t}} = 0$, for all t.

$$g_{G_{c,h,t}} = \begin{cases} u_{c,h,t} & \text{iff } \ln G_{c,h,t-1} + u_{c,h,t} \in [a_h, b_h] \\ a_h - \ln G_{c,h,t-1} & \text{iff } \ln G_{c,h,t-1} + u_{c,h,t} < a_h \\ b_h - \ln G_{c,h,t-1} & \text{iff } \ln G_{c,h,t-1} + u_{c,h,t} > b_h \\ 0 & \text{otherwise} \end{cases}, \tag{5}$$

$$u_{c,h,t} \sim N\left(\mu_{g_{G_h}}, \sigma^2_{g_{G_h}}\right), \tag{6}$$

where $\mu_{g_{G_h}}$ and $\sigma^2_{g_{G_h}}$ denote the mean and variance of the Gini coefficient growth, respectively, and a_h and b_h respectively symbolize the lower and upper bounds of the Gini coefficients per country typology—in logarithmic terms. The coefficients a_h and b_h can be proxied by the first and largest order statistics of recorded Gini coefficients, respectively. In addition, note that the thresholds a_h and b_h and the random behavior of the growth rates of the Gini coefficient, $u_{c,h,t}$, vary by country typology h.[20,21]

Our econometric considerations do not model an explicit association between growth in the Gini coefficient and growth in the mean income. The degree of association of the Gini coefficient growth rate with the average annual growth rate of per capita consumption, GDP per capita, and mean income—measured through Pearson's correlation coefficients—is almost null across country classifications.[22] Thus, we argue that there is not enough information yet to provide evidence of covariance between growth in the Gini coefficients and growth in the mean income.

[20] One moderate alternative of the modeling of Equation (5) would not let $\ln G_{c,h,t}$ reach the thresholds a_h and b_h. Thus, Equation (5) could be estimated following this specification:
$g_{G_{c,h,t}} = \begin{cases} u_{c,h,t} & \text{iff } \ln G_{c,h,t-1} + u_{c,h,t} \in [a_h, b_h] \\ 0 & \text{otherwise} \end{cases}$.

[21] One conservative alternative to Equation (6) involves modeling the rate of change in the Gini coefficient following a truncated normal distribution: $u_{c,h,t} \sim TN\left(\mu_{g_{G_h}}, \sigma^2_{g_{G_h}}, \pi_0, \pi_1\right)$, where, $TN(\cdot)$ represents a univariate truncated normal distribution with mean $\mu_{g_{G_h}}$, variance $\sigma^2_{g_{G_h}}$, and lower and upper bounds π_0, and π_0, respectively.

[22] We account for four important results regarding Pearson's correlation coefficients pooling our original 1980–2014 observations by the studied country classifications. First, the significant correlation coefficients of the average growth rate of the Gini coefficient and the average growth rate of per capita consumption vary between -0.077 and -0.048 across the studied country categories. Second, in the case of the growth rate of the Gini coefficient and the growth rate of GDP per capita, all the correlation coefficients are found nonsignificant across the country classifications whereas they vary close to zero in magnitude: from -0.68 to 0.067. Third, few significant correlation coefficients between the Gini coefficient growth rate and the growth rate of the mean income are found across the country typologies: 0.14 pooling all country observations, 0.181 for NROC economies, 0.16 for MOGCs, and 0.4 for LOGCs. Fourth, all the correlation coefficients of the growth rate of the Gini coefficient and the growth rate of the mean income become almost null and/or statistically nonsignificant across the study typologies when we complete our 1980–2014 panel data set using per capita consumption growth rates—or GDP per capita growth rates in the alternative case.

Hence, our model—and subsequent simulations—assumes there is no covariance between these two variables: $cov\left(g_{c,t}, g_{G_{c,h,t}}\right) \approx 0$.

C. Aggregations

We aggregate country-specific Gini coefficients to explain the average outcomes across country classifications, h. Our aggregated Gini coefficient, $G_{h,t}$, is a population-weighted average of country Gini coefficients,

$$G_{h,t} = \frac{1}{n_{h,t}} \sum_{\forall c \in C_h} n_{c,t} G_{c,t}, \text{ for all country classifications, } h, \tag{7}$$

where the total population of the specific country typology h in period t is denoted by $n_{h,t}$, and the population in country c at period t is represented by $n_{c,t}$.

We also estimate the aggregated shared prosperity measures by country classifications. The shared prosperity gap requires subtracting the growth rate of the mean, or any percentile of the income distribution, from the 40th percentile of the income distribution. Specifically, the comparison of the growth rates between the B40 of the income distribution and the statistic $s_{Y_{c,t}}$ across countries is estimated via the following weighted gap:

$$D_{h,t}^{B40-s_{Y_{c,t}}} = \frac{1}{n_{h,t}} \sum_{\forall c \in C_h} n_{c,t} \left(g_{p_{Y_{c,t}}^{40}} - g_{s_{Y_{c,t}}} \right), \tag{8}$$

for all country classifications, h, and the mean and k percentile of income, $s_{Y_{c,t}}$=$\{\mu_{Y_{c,t}},\ p_{Y_{c,t}}^{k}\}$. Note that $g_{p_{Y_{c,t}}^{40}}$ denotes the annual growth rate of the 40th percentile of the distribution of $Y_{c,t}$, while the corresponding rate for $s_{Y_{c,t}}$ is denoted by $g_{s_{Y_{c,t}}}$.

III. Country Typologies

Two typologies are used to describe economies with large output shares of natural resource activities—extractive sectors—and to denote the importance of economic growth (Table 1). Although arbitrarily selected, our country typologies aim to capture substantial deviations from the results with global scope. In specific, our typologies look at deviations in terms of future

poverty attainments and income distribution changes to underline the heterogeneity of countries in our sample. The first classification includes countries with historically substantial natural resource rents, as a share of gross domestic product.[23] ROC economies are those above the 90th percentile of country observations of resource rents in the period 1970–2015. In contrast, NROC—or more-diversified—economies are those with smaller shares of natural resources. The second typology comprises economies in three sub-categories based on rates of growth of output per capita in recent decades. We define thresholds for GDP per capita growth rates using cross-country sample statistics between 1970 and 2014. These selected thresholds are the 30th and 70th percentiles of pooling all our country GDP per capita growth rates in the period 1970–2014.[24]

TABLE 1. COUNTRY CATEGORIES

Category	Descriptor	Definition	Country examples
ROCs	Resource output-oriented countries	$\tilde{R} \geq \mathrm{p}^{90}_{\mathrm{R}_{70-15}}$	Algeria, Cameroon, Myanmar, and Venezuela.
NROCs	Non-resource output-oriented countries	$\tilde{R} < \mathrm{p}^{90}_{\mathrm{R}_{70-15}}$	Argentina, Finland, Japan, and Vietnam
LOGCs	Low-output growth countries	$\tilde{g}_y \leq \mathrm{p}^{30}_{\mathrm{y}_{70-15}}$	Haiti, Madagascar, Niger, and Zimbabwe
MOGCs	Middle-output growth countries	$\mathrm{p}^{30}_{\mathrm{y}_{70-15}} < \tilde{g}_y \leq \mathrm{p}^{70}_{\mathrm{y}_{70-15}}$	Belgium, Ecuador, Nigeria, and Pakistan
HOGCs	High-output growth countries	$\tilde{g}_y > \mathrm{p}^{70}_{\mathrm{y}_{70-15}}$	Bulgaria, Chile, China, and South Korea

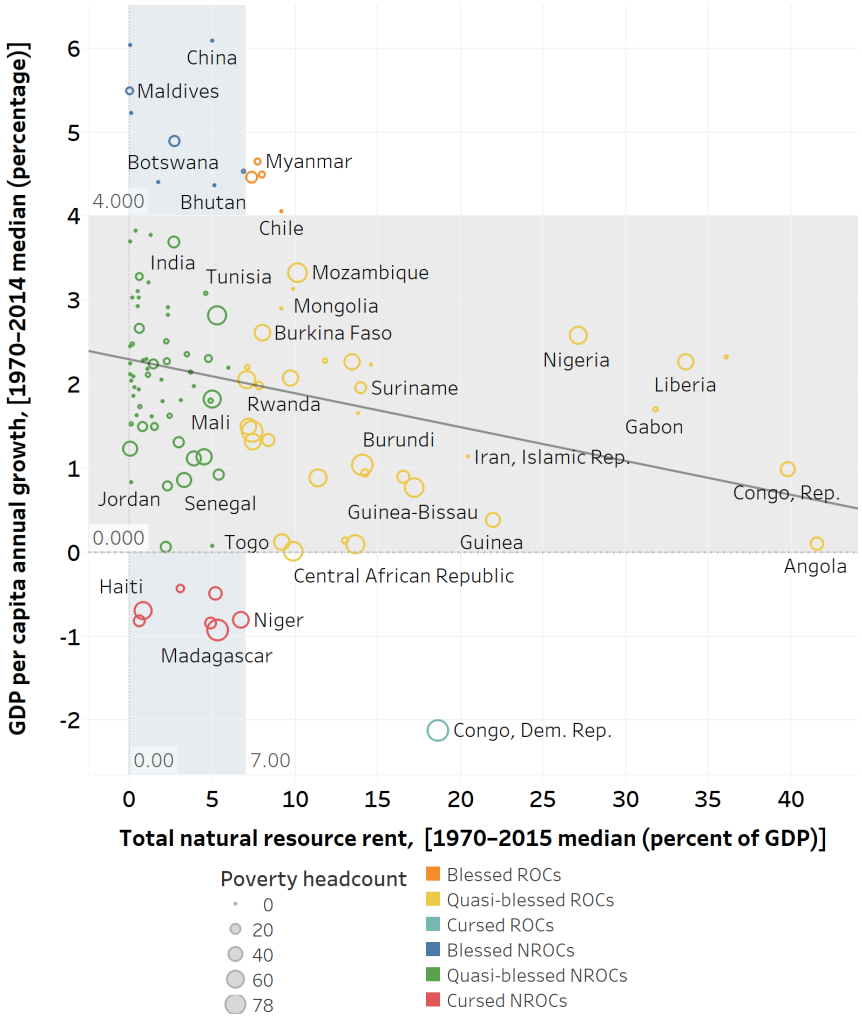
Source: Penn World Table 9.0, World Development Indicators, United Nations, and the author's estimates. *Note:* $\tilde{\mathrm{R}}$ denotes the median value of resource rents as a percentage of GDP over the period 1970–2015 pooling all country information. The median cross-country value of GDP per capita growth—in percent—over the period 1970–2014 is represented by $\tilde{g}_y$. GDP per capita data in purchasing power parity (PPP) 2011 U.S. dollars. In practice, the selected percentiles of output per capita are rounded to 0 and 4, i.e., $\mathrm{p}^{30}_{\mathrm{y}_{70-15}} \approx 0$, and $\mathrm{p}^{70}_{\mathrm{y}_{70-15}} \approx 4$. The 90th percentile of the natural resource rents as a percentage of GDP is rounded to 7, $\mathrm{p}^{90}_{\mathrm{R}_{70-15}} \approx 7$. For robustness purposes, the estimates presented in the results section are tested varying the thresholds that define ROCs, NROCs, LOGCs, MOGCs, and HOGCs, i.e., varying $\mathrm{p}^{90}_{\mathrm{R}_{70-15}}$, $\mathrm{p}^{30}_{\mathrm{y}_{70-15}}$ and $\mathrm{p}^{70}_{\mathrm{y}_{70-15}}$.

By combining both typologies, Figure 1 summarizes the median behavior of output per capita growth and natural resource rent shares across countries over the period 1970–2014 and 1970–2015. Figure 1 shows what some authors have already argued: some countries might look cursed, while others might appear to be blessed by having significant shares of natural resource

[23] This paper follows the definition of natural resource rents used in World Bank (2017): natural resource rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. For instance, natural gas rents are the difference between the value of natural gas production at regional prices and total production costs.
[24] The thresholds that define these two country typologies are varied to test the robustness of our simulated outcomes as described in Subsection IV of the results (Section VI).

output or exports (Crafts and O'Rourke 2014). In Figure 1 we also observe two different poverty headcount performances across countries. First, most countries with abundant natural resource rents in the period 1970–2015 have issues with high extreme poverty headcounts. Second, countries with current high poverty headcounts are those for which the median annual growth rates of GDP per capita in the period 1970–2014 are below the 4 percent threshold, or in other words, those countries that could not attain high-output growth rates in a more consistent form in the study period.

FIGURE 1. GDP PER CAPITA GROWTH, NATURAL RESOURCE RENTS, AND POVERTY



Source: Penn World Table 9.0, World Development Indicators, PovcalNet, United Nations, and the author's estimates. *Note:* GDP per capita data in purchasing power parity (PPP) 2011 U.S. dollars. PovcalNet poverty headcount observations using the international poverty line of $1.90/day in 2011 PPP U.S. dollars. The sample used in this figure includes 148 countries, each with more than 44 annual observations of GDP per capita over the period 1970–2014. Table 1 provides details of the thresholds used in this figure.

Definitions used in Table 1 split Figure 1 into six country classifications. First, the Democratic Republic of Congo faced negative growth—a median estimate between 1970 and 2014 observations—while having significant resource rents, which in this context indicates it is a cursed resource rent economy.[25] Second, countries with a small share of resource rents also experienced negative output growth. Labeled as cursed non-resource rent economies, Haiti and Djibouti are examples of this negative growth and significant resource rent performance. Third, countries with substantial resource rents such as Chile had median rates higher than 4 percent over the period 1970–2015 and are tagged as blessed resource-based countries. Fourth, countries with unimportant natural resource rents—such as Belarus and the Republic of Korea—still perform with high median GDP per capita rates which in these circumstances are denoted as blessed non-resource rent countries. Fifth, quasi-blessed resource rent economies performed with moderate median growth rates and significant resource rents, such as Cameroon and the Islamic Republic of Iran. Sixth, there is a set of countries with reasonable median growth rates and small resource rents; these are called quasi-blessed non-resource rent economies, e.g., Bolivia and Kenya.[26]

IV. DATA

The projections of future poverty and income distribution changes are performed based on sample statistics derived from information of mean income, Gini coefficient, population, per capita consumption or GDP per capita, commodity prices, and purchasing power parity (PPP) prices. We present some descriptive statistics of these variables by country typologies for the period 1980–2014 in Table B 2 in Appendix B.

For the first country typology, the pooled country information indicates that more-diversified economies—NROCs—have, on average, a much larger mean income than resource-output oriented economies. For our second typology, MOGCs have, on average, a higher mean income than HOGC and LOGC economies; the LOGC economies have, on average, the lowest mean income during the study period.

[25] According to Sachs and Warner (2001), the natural resource curse implies that countries with considerable natural resource wealth tend to grow at a slower pace than resource-poor economies.
[26] To denote the strength of the relationship pointed out in Figure 1, we highlight in Figure D 1, Appendix D some stylized facts of GDP per capita growth and natural resource rents across decades.

In terms of income inequality, on the one hand, ROCs present, on average, higher values in the Gini index than NROCs—a difference of more than 2 percent. On the other hand, LOGCs, on average, have higher total income inequality, while HOGCs present the lowest. There is a substantial difference of 7 percent between the average Gini coefficient of LOGC and HOGC economies.

V. SIMULATION

Our simulation procedure permits to make a dynamic assessment of income distribution by country. The Monte Carlo simulation method combines multiple paths of mean income growth with a variety of inequality trajectories to predict changes in income distribution. The practical exercises described in the sections below use household survey data of incomes and expenditures in the period 1980–2015.[27,28] Thus, given the scarcity of microdata for the study period, per capita consumption growth is initially used to construct synthetic observations of mean income between spells. As an alternative, GDP per capita growth was tested and used instead of per capita consumption growth.

The Monte Carlo simulation procedure consists of deriving simulated paths of the mean income and the Gini coefficient. To recover these paths, at each period $t = \{2015,\ 2016, \dots, T\}$, n number of random draws are generated to complete the simulated sequences. These sequences consist of global mean income growth $\{\{g_{2015}\}_{k=1}^{n}, \dots, \{g_T\}_{k=1}^{n}\}$, global real commodity prices $\{\{p_{2015}\}_{k=1}^{n}, \dots, \{p_T\}_{k=1}^{n}\}$, idiosyncratic shocks in the mean-income growth $\left\{\{\varepsilon_{c,2015}\}_{k=1}^{n}, \dots, \{\varepsilon_{c,T}\}_{k=1}^{n}\right\}$, and idiosyncratic shocks in the growth of the Gini coefficient $\left\{\{u_{c,2015}\}_{k=1}^{n}, \dots, \{u_{c,T}\}_{k=1}^{n}\right\}$. Each draw is generated using mean and variance sample statistics for a specific period.

Although the simulation exercises are designed to be comprehensive and to project multiple and simultaneous performances of factors affecting the countries' mean income growth, our model is simple by design and includes some caveats. Four core elements considered when we

[27] Data were retrieved on February 22, 2019 from PovcalNet (World Bank 2019).

[28] A priori, given the embedded historical information in the period 1980–2015, country-specific simulations are expected to be much closer to the idea of inequality convergence; this means that inequality tends to decrease in countries with high inequality and increase in countries with low inequality (Benabou 1996, and Ravallion 2003).

analyze the results of the Monte Carlo simulations. First, there is the potential issue of misspecification of the econometric model, Equation (1). The econometric specification of mean income growth could be affected by omitted factors: global and country-specific components. Additionally, some of the factors affecting mean income growth might not respond to a linear form.

Second, the probability distribution assumptions may affect the variables used to predict the future behavior of the country mean income growth. Global growth and commodity prices could entail more complicated distributions with longer tails. In the same vein, the idiosyncratic error terms could have a long-tailed distribution or skewed parameterization instead of a normal distribution arrangement. Thus, our projections of mean income growth may not capture tail behaviors. In the same vein, given a lack of observations for the Gini coefficient across countries over the study period 1980–2014, the bounded random walk stochastic process assumption that models the logarithm of the Gini coefficient could entail a very restrictive specification.

Third, country-level statistics are based on household data that incorporate multiple sources of errors. For instance, collected household observations could include sampling and non-sampling measurement errors. Although the number of household surveys has expanded in countries around the world, the frequency and quality of the collected information vary greatly, which may cause problems related to the consistency and comparability of the data between and within countries (World Bank 2014, Chapter 5). Fourth, demographic trends that account for changes in the total population might have some degree of uncertainty, especially in terms of the materialization of a significant factor such as war, massive migration, or an epidemic (United Nations 2017).

VI. RESULTS

This section presents our simulated outcomes of poverty and changes in the income distribution for the period 2015–2030. All our results are analyzed at the global level and by the country typologies introduced in Table 1. Subsections A and B discuss poverty headcount and relative income inequality estimates, respectively. In Subsection C, we analyze the speeds of the B40 percent relative to other percentile growth rates of the income distribution—shared prosperity

gaps.[29] In Subsection D, we present the robustness checks. We use the robustness exercises to test for factors that can lead to heterogeneity in the simulation results: the sample period, the thresholds that define the country typologies, and alternative measures for mean income growth rates.

A. Poverty Headcount

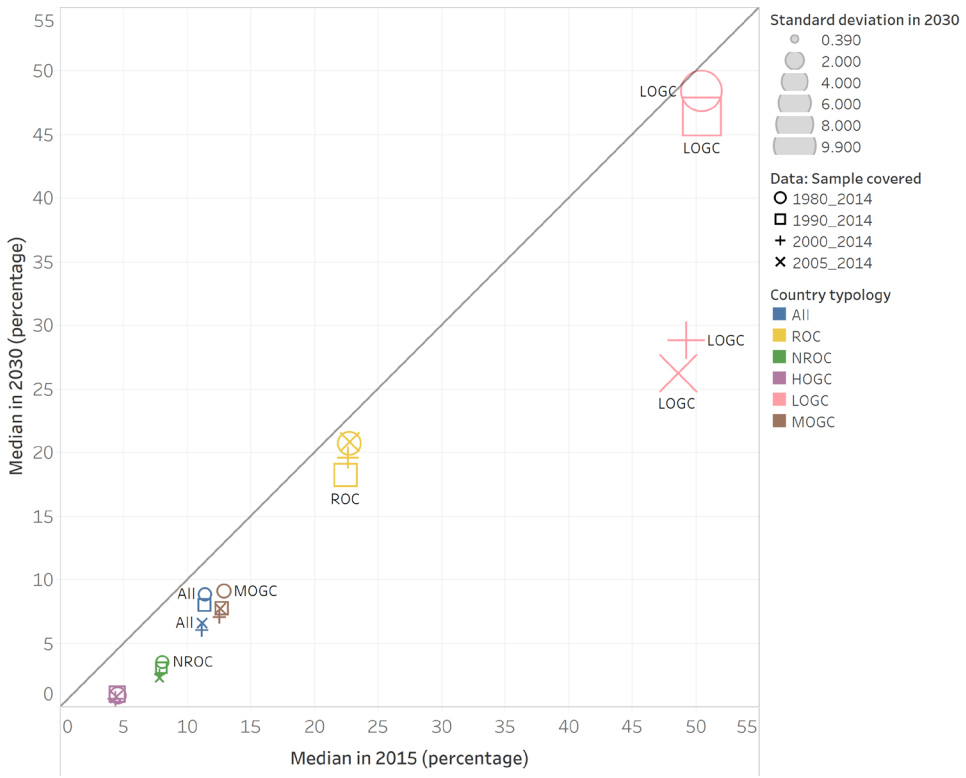
Our results show that the poverty headcount projections vary substantially depending on the selection of the base period of the simulations (Figure 2).[30,31] These predicted median estimates of global poverty headcount for 2030 are 8.8, 8.0, 6.1, and 6.6 percent; these are the simulation outcomes based on country-samples for the periods 1980–2014, 1990–2014, 2000–2014, and 2005–2014, respectively. Our global poverty estimates show that a substantial decline in global poverty is very likely by 2030, both in relative and absolute terms (Figure 2 and Figure 3). When comparing the simulated median values, global poverty headcount is predicted to decline between 3 and 5 percent—or, in other words, between 80 million and 300 million people—in the 2015–2030 period. These median estimates, however, are insufficient to reach the global target of 3 percent for extreme poverty headcount by 2030. Our empirical distribution of simulated outcomes suggests that the global 3 percent poverty target is reachable in 2030 with a probability of less than 2 percent (see Figure A 1, Panel A, Appendix A).

While the reduction in world poverty in the last 35 years is a significant achievement, its continued eradication in the following decades is expected to remain a substantial concern. If we consider the recent historical observations of income growth, inequality dynamics, and commodity prices to be useful information to predict the future performance of the income distribution, then our expectations for reducing poverty below the 3 percent threshold by 2030 should be very optimistic. To accelerate growth across the income distribution, we can explore alternative

[29] The outcomes reported in Subsections A, B and C are based on per capita consumption growth rates, which were used to complement the country observations for household survey mean income or expenditures present in PovcalNet.
[30] The poverty estimates use the $1.90 international poverty threshold in purchasing power parity (PPP) 2011 international U.S. dollars per day.
[31] The detailed list of countries used in the simulations is provided in Table B 1 in Appendix B.

mechanisms to fuel growth across nations and monitor countries where poverty rates are predicted to be a significant problem.[32]

FIGURE 2. POVERTY HEADCOUNT RATES



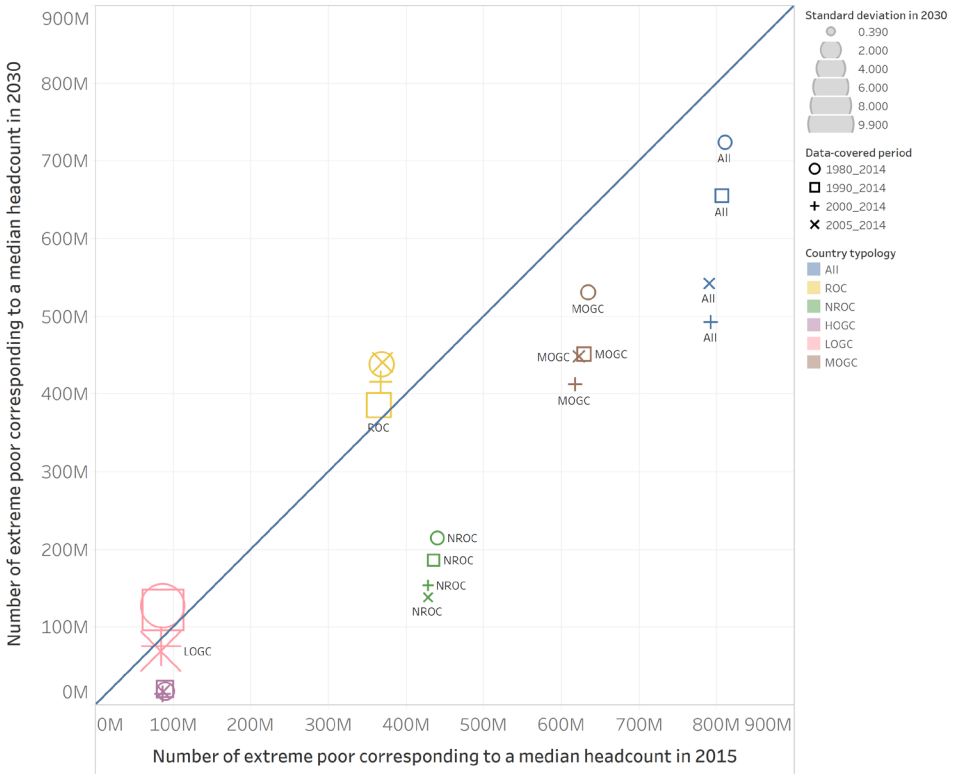
Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditures in the household survey observations. Projected country population weights the estimates. A total of 500 simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014. The standard deviation corresponds to that associated with poverty headcount simulated outcomes in 2030.

The uncertainty around our 2030 predicted estimates of global poverty—measured by the standard deviation of the simulated paths—indicates conservative values with magnitudes of 0.9, 1.0, 0.9, and 0.6 percentage points for the same four sample periods, 1980–2014, 1990–2014, 2000–2014, and 2005–2014, respectively. The positive skewness of the poverty headcount simulations—using the 1980–2014, 1990–2014 and 2000–2014 sample periods—implies more

[32] Based on the standard variance decompositions of Equation (1) presented in Figure C 2 in Appendix C, we presume that mechanisms that foster idiosyncratic country characteristics are key for boosting mean income/expenditure growth.

substantial downside than upside risks. In contrast, the simulated outcomes of poverty headcount for 2005–2014 are slightly skewed to the upside.[33]

FIGURE 3. ABSOLUTE EXTREME POVERTY



Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditures in the household survey observations. Projected country population weights the estimates. A total of 500 simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014. The standard deviation depicts that associated with the poverty headcount simulations in percentage as presented in Figure 2. "M" in the X and Y axes denotes million.

ROCs and NROCs. The simulated results indicate that poverty headcount rates will most likely continue declining in both ROCs and NROCs to 2030. In 2015, the estimated rates of poverty headcount in ROCs and NROCs were approximately 22 and 8 percent, respectively. By 2030, ROCs and NROCs will likely achieve average poverty headcounts of 20 and 3 percent, respectively (see Figure 2 and Figure A 2 in Appendix A). In absolute terms, NROCs could lift between 225 million and 290 million people out of extreme poverty in the period 2015–2030. In contrast, there is a significant likelihood that ROCs will see an increase in the number of people

[33] For the poverty headcount rates, a negative skewness value indicates that the distribution is skewed to the upside.

living in extreme poverty by between 20 million and 70 million over the same projected period (Figure 3).

The set of simulations focused on ROCs and NROCs predicts 2030 poverty headcount results with uncertainty—the standard deviation of simulated outcomes—at 2.9 and 0.6 percent, respectively. By 2030, on average and across the four studied sample periods, the ratio of this uncertainty between ROCs and NROCs is approximately 5 to 1. This comparison of the size of the uncertainty between ROCs and NROCs shows how difficult it is to predict the poverty headcount performance of resource-output oriented economies; this is in line with the recent historical variability of economic growth in ROCs and NROCs (Figure D 2 in Appendix D).[34]

LOGCs, MOGCs, and HOGCs. The estimates of the 2015 poverty headcount in LOGCs, MOGCs, and HOGCs was approximately 50, 13, and 4 percent, respectively. The predictions of poverty in LOGCs in 2030 are quite susceptible to the sample period used to generate the Monte Carlo simulations (Figure 2). Using the 1980–2014 and 1990–2014 sample periods, the LOGCs are expected to decrease their poverty headcount by 2 and 4 percentage points, respectively, in the period 2015–2030. Using better performance periods of growth (2000–2014 and 2005–2014), LOGCs expect, in terms of the median values, to reduce their initial 2015 poverty headcount rates by more than 20 percentage points in the 2015–2030 horizon. In contrast, extreme poverty in absolute terms in LOGC economies over the horizon 2015–2030 is predicted to either increase by more than 30 million under the 1980–2014 and 1990–2014 sample periods or to decrease on average more than 9 million people under the 2000–2014 and 2005–2014 base periods. The simulations for the MOGC economies show more consistent results of poverty headcount hovering around median values between 7 and 9 percent by 2030. These poverty rates correspond to a decline in extreme poverty by 200 million and 100 million people between 2015 and 2030, respectively. HOGCs, in contrast, expect to decrease their poverty headcount rates, in terms of the median simulated outcomes, to levels of approximately 1 percent in 2030, lifting around of 70 million people out of extreme poverty conditions in the same 2015–2030 horizon.

Likewise, the uncertainty associated with the poverty headcount predictions for 2030 varies significantly depending on the country-output growth subcategory. Regardless of the study period,

[34] Among the four studied sample periods, the information embedded in the period 2005–2014 (global pre- and post-financial crisis period) leads to simulated outcomes of the poverty headcount with less dispersion—uncertainty—for both country typologies, ROCs and NROCs.

the predictions indicate that LOGCs have higher embedded uncertainty in poverty outcome attainments, followed by the HOGCs and MOGCs (see Figure 2 and Figure A 4 in Appendix A). The average standard deviations of the poverty predictions for 2030 are 9.4, 0.9, and 1.3 percent for the LOGCs, MOGCs, and HOGCs, respectively; this outcome shows the degree of difficulty predicting poverty rates in LOGCs.

B. Income Inequality

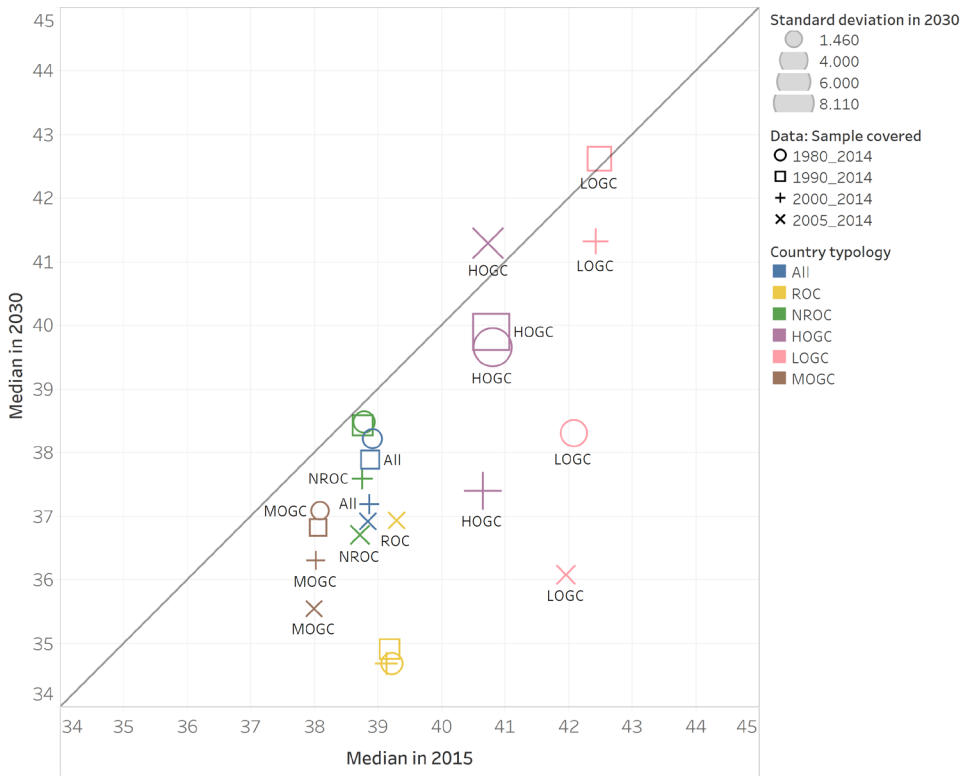
Our main result suggests that global income inequality will decline over the period 2015–2030 (Figure 4). Our simulated aggregate of the global Gini coefficient fluctuates from a median of 38.9 in the Gini scale of 0–100 in 2015 to a median of 37.5 by 2030 across the four study periods. Specifically, the results for the population-weighted average indicate reductions in global income inequality between 0.7 and 1.9 Gini points in the period 2015–2030. Panel B of Figure A 1 in Appendix A presents the estimated trend of this global aggregate of the Gini coefficient since 1980. Our model also captures substantial uncertainty in the projected global Gini coefficient outcomes. This attached uncertainty hovers between 1.6 and 2.1 Gini points in 2030.

ROCs and NROCs. Note that in the period 1990–2014, the ROC economies experienced a decrease in inequality by more than 2 Gini coefficient points. Similarly, our estimates for the ROCs reveal a downward trend in our simulated projections over the 2015–2030 horizon. Overall, these results show that income inequality will decrease in ROCs, in terms of the median values, between 2.4 and 4.5 Gini coefficient points in the period 2015–2030. We expect the same median pattern in NROCs, but the magnitude of the decline in inequality could be smaller: between 0.3 and 2.0 Gini points over the 2015–2030 horizon (see Figure 4 and Figure A 3 in Appendix A). The results of the uncertainty attached to the projected paths of the aggregated Gini coefficient have similar magnitudes—approximately 2.2 Gini points—for ROCs and NROCs by 2030. The simulations indicate that by 2030, there are significant downside risks in NROCs, such that these economies are expected to see increased income inequality (see Figure 4 and Figure A 3 in Appendix A).

LOGCs, MOGCs, and HOGCs. By 2030, the estimated Gini coefficient for LOGCs, MOGCs, and HOGCs is predicted to vary across a broad spectrum of values (Figure 4). The aggregated Gini coefficient for LOGCs and MOGCs could decrease up to 5.9 and 2.5 Gini points, respectively, in terms of the median values, over the 2015–2030 horizon. On the opposite direction, the estimation

based on the period 1990–2014 shows that the Gini coefficient could increase by 0.1 Gini points in LOGC economies over the same horizon. Unevenly, HOGCs show three simulation outcomes where the Gini coefficient could decrease between 3.3 and 0.9 Gini points in the period 2015–2030. In contrast, the simulation based on 2005–2014 indicates an increase in income inequality in HOGCs by 0.5 Gini points (see Figure A 5 in Appendix A).

FIGURE 4. GINI COEFFICIENT



Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditures in the household survey observations. Projected country population weights the estimates. A total of 500 simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014. The standard deviation depicts that associated with the aggregated Gini coefficient which ranges from 0–100.

Besides, the uncertainty in the estimated Gini coefficient is smaller in MOGCs than in LOGCs and HOGCs, with HOGC economies showing the largest dispersion of simulated outcomes. The uncertainty attached to the predicted Gini coefficient aggregations has an average standard deviation of 3.2, 1.6 and 7.3 Gini points in LOGCs, MOGCs, and HOGCs, respectively (Figure 4).

C. Shared Prosperity Gaps

The simulations of the global estimates of shared prosperity gaps between the B40 and the mean and $p_{Y_{c,t}}^{50}$, $p_{Y_{c,t}}^{60}$, $p_{Y_{c,t}}^{70}$, and $p_{Y_{c,t}}^{80}$ percentiles, show that the average and median simulated outcomes—estimated by Equation (8)—are all positive in magnitude over the period 2016–2030.[35] Figure 5 shows the specific results of the B40–median shared prosperity gap. For instance, the median outcomes generated by using the 1980–2014 base period suggest that at the global level the B40 might be growing 2.9 percentage points faster than the median of the income distribution by 2030.

ROCs and NROCs. For this country typology, we distinguish two main patterns in the set of simulations of shared prosperity gaps. The first pattern—based on median outcomes—indicates that the B40 is expected to grow at faster rates, on average, than higher percentiles of the income distribution across both country classifications (ROCs and NROCs) by 2030 and throughout the period 2015–2030 (Figure 5). However, a second pattern shows that the outcomes of shared prosperity measures in both types of economies (ROCs and NROCs) present a more positive standard deviation, or uncertainty, as the difference between percentiles increases.[36]

LOGCs, MOGCs, and HOGCs. Our simulated shared prosperity gaps for LOGCs, MOGCs, and HOGCs show uneven patterns. We identify four main results that shape our shared prosperity measures. The first main pattern indicates that, in terms of the median values, the shared prosperity gaps in MOGCs increase as the difference between the B40 and the studied percentiles, $p_{Y_{c,t}}^{50}$, $p_{Y_{c,t}}^{60}, p_{Y_{c,t}}^{70}, p_{Y_{c,t}}^{80}$, also increases. Note that the shared prosperity gaps in the MOGC simulations always have a positive sign. The second major outcome indicates that in terms of the median values, the absolute value of the shared prosperity gaps in LOGCs and HOGCs increases as the difference between the B40 and the studied percentiles expands; this pattern means that depending

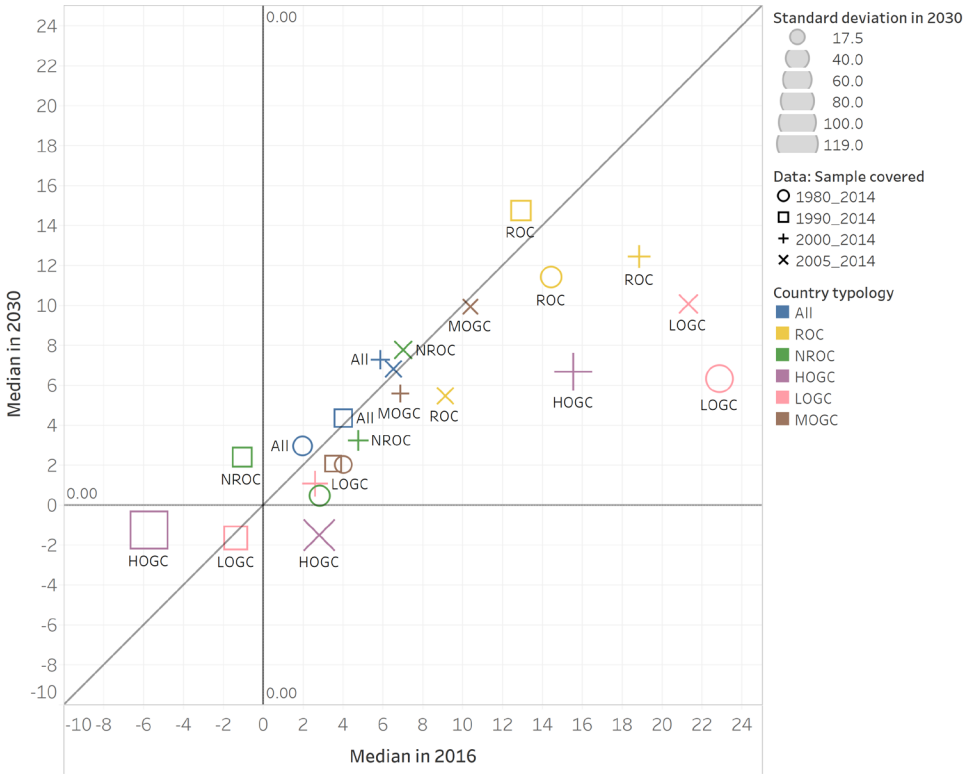
[35] Note that the studied shared prosperity gaps are: $D_{h,t}^{B40-mean}$, $D_{h,t}^{B40-p_{Y_{c,t}}^{50}}$, $D_{h,t}^{B40-p_{Y_{c,t}}^{60}}$, $D_{h,t}^{B40-p_{Y_{c,t}}^{70}}$, and $D_{h,t}^{B40-p_{Y_{c,t}}^{80}}$. Additional statistics of these simulated shared prosperity gaps are available upon request.

[36] Based on our selected shared prosperity gaps, this second pattern means that the gap in the growth rate between the B40 and the 80th percentile, $p_{Y_{c,t}}^{80}$, has the most uncertainty, whereas the gap that compares the B40 with the median, $p_{Y_{c,t}}^{50}$, has the least amount of uncertainty.

on the period used to generate the simulations, LOGCs' and HOGCs' shared prosperity gaps could be either positive or negative.

The third leading result indicates that across the three output growth country classifications, the standard deviation of the simulated shared prosperity gaps increases as the B40 moves away from closest percentiles of the income distribution. As in the case of the ROCs, NROCs, and global outcomes, this result indicates that our model is predicting noisier—or more uncertain—outcomes of shared prosperity gaps as the studied percentile moves further from the B40. Finally, the fourth important outcome shows that MOGCs and HOGCs have the lowest and highest uncertainty—dispersion—on their predicted shared prosperity gaps across the three output growth country classifications, respectively (Figure 5).

FIGURE 5. B40 – MEDIAN - SHARED PROSPERITY GAP



Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditures in the household survey observations. Projected country population weights the estimates. A total of 500 simulations are performed per country and forecasted period. The simulations use 4 sample periods to test the robustness of the results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014. The standard deviation depicts that associated with the B40–median shared prosperity gap simulations as a percentage.

D. Robustness Checks

We test for three main dimensions that may impact our simulation outcomes: the study periods, the country typology definitions, and the mean income growth rates. First, as reported in the previous subsections, we vary the base period of the simulations to check the robustness of our predictions. Despite differences in outcomes, the results for extreme poverty, the Gini coefficient, and the shared prosperity measures in ROCs, NROCs, and MOGCs vary conservatively across the studied sample periods. Regarding extreme poverty in relative terms, the main discrepancies are in the simulated results for the LOGCs, with levels ranging from 25 to 50 percent by 2030 (Figure 2). In terms of absolute extreme poverty, the main variation in the outcomes in 2030, in terms of median values, can be observed in the global—all countries—classification, with results ranging from 490 million to 725 million people across the study periods (Figure 3). Regarding the Gini coefficient estimates, the HOGCs and LOGCs show dispersed effects such that their estimated median values for 2030 hover between 37 and 40, and 36 and 42, respectively, across the four studied sample periods (Figure 4). Regarding the shared prosperity gaps, the main differences in the 2030 median predictions within country typologies are found in HOGCs and LOGCs (Figure 5).

Second, we redefine the country typologies in Table 1 by varying the thresholds that define these classifications. Our new simulations add and subtract 0.3 percentages points to the boundaries described in Table 1 for both natural resource rent and output growth country classifications. The change in the boundaries shown in Table 1 confirms that countries near the threshold definitions are not driving the results, as we can observe in the estimates for extreme poverty and the Gini coefficient (see Figure A 6 and Figure A 7 in Appendix A). These changes in the boundaries lead to a higher degree of certainty in the outcomes for extreme poverty and the Gini coefficients discussed in the previous subsections and depicted in Figure 2–Figure 4. Despite similar magnitudes in median values and standard deviations, the simulated shared prosperity gaps differ within country typologies in terms of direction when comparing the results presented in Figure 5 with those in Figure A 6, Panel D and Figure A 7, Panel D, Appendix A.

Third, as an additional robustness check of the simulated outcomes, given the scarcity of country microdata, instead of using the growth rate of household expenditures per capita to construct the synthetic observations of mean income/expenditures between spells, the model is

tested using the GDP per capita growth rate. We re-estimate our simulations for the study periods and country classifications incorporating GDP per capita growth information (the results are summarized in Figure A 8 in Appendix A). These new results are consistent with those reported in previous sections with similar magnitudes and directions. The main difference is that extreme poverty is reduced by a more significant proportion in 2030 when using GDP per capita growth rates (see Figure A 8, Panel A and B, Appendix A) compared to the outcomes obtained using consumption growth rates (see Figure 2 and Figure 3).

VII. CONCLUSIONS

This research contributes to the discussion on future economic growth, poverty, inequality, and shared prosperity measures. Our analysis exploits two country typologies to show heterogeneity of predictions and uncertainty in poverty outcomes and income distribution conditions. The first typology splits the economies by the size of their natural resource sectors. The second country classification relies on the speed of the output per capita growth. Although our typologies are arbitrary, our results and robustness checks suggest that these studied country classifications matter significantly in poverty eradication and income distribution attainments, possibly capturing and indicating institutional quality. The primary finding of this paper shows a significant level of uncertainty in future poverty and income distribution achievements at the global level and by country classifications. One important caveat of the article is that our predictions are based on recent historical performances. This recorded history used in our simulations suggests that countries performing poorly—in terms of future poverty reduction and shared prosperity attainments—should emphasize efforts to implement policies that boost economic growth and provide social safety nets as a hedging mechanism, especially in the most impoverished and unprotected sectors of their societies.

We summarize the three main results of this study. The first significant insight is related to the predicted poverty headcount. The results indicate that despite the continuous decrease in relative and absolute poverty, alleviating extreme poverty below the 3 percent threshold by 2030 is very optimistic at the global level and involves considerable uncertainty. The simulations generated by combining the information from the 2000–2014 sample period with GDP per capita growth rates—which were used to complement the household survey mean income

observations—provide the most positive results for decreasing extreme poverty by 2030: median value of 4.6 percent or 371 million people in relative and absolute terms, respectively. In contrast, the simulations derived by combining data from the 1980–2014 base period with growth rates of per capita consumption provide the worst predictions for global poverty reduction by 2030: median value of 8.9 percent or 724 million people in relative and absolute terms, respectively.

Non-resource-output oriented economies, however, are predicted to achieve and even surpass the 3 percent poverty target by 2030. Although extreme poverty is expected to diminish in relative terms, in several simulation exercises, resource-output oriented economies could see an increase in absolute poverty over the period 2015–2030. Note that there is significant variability in the predicted future poverty outcomes for resource-output oriented countries, implying that given recent historical economic episodes, it is hardly possible to predict precise estimates of poverty rates in these economies. Moreover, poverty is expected to decline in the period 2015–2030 in relative terms in low-output, middle-output, and high-output growth country categories. Nevertheless, poverty in low-output growth economies is expected to increase in absolute terms. The results show that the high dispersion—low precision—in the simulation outcomes denotes some inability to predict poverty outcomes in countries classified as low-output growth economies. The model simulations predict that high-output growth economies will quickly alleviate poverty below the 3 percent level before 2030. Noticeably, the simulations show a low degree of uncertainty in the expected poverty outcomes of countries with high-output growth rates.

The second main result indicates that changes in relative income inequality are predicted to be on the positive side, meaning that in general, the Gini coefficients across the studied country classifications are predicted to decrease on average over the period 2015–2030. Across this 2015–2030 horizon, our estimates of the Gini coefficient at the global level are expected to decline between 0.7 and 1.9 Gini points (in the Gini scale of 0–100). The simulation outcomes suggest some degree of uncertainty such that non-resource-output oriented countries and low-output and high-output growth countries could either decrease or increase their income inequality levels across the period 2015–2030.

The third significant result indicates that the B40 of the income distribution is, on average, predicted to grow faster than the mean and higher percentiles over the 2015–2030 horizon and across the studied country aggregations. There are a few simulations, however, with median values

indicating that the B40 could grow at lower speeds than the higher percentiles; see the cases for the resource-output oriented, low-output and high-output growth countries. Notably, there is an extensive range of uncertainty in all simulated shared prosperity gaps. The larger the distance between the bottom 40 and upper-income percentiles, the more positive the magnitude of the standard deviation of the simulated outcomes; these results hold across the studied country categories.

In comparison with point predictions and perfect-foresight methods, our proposed approach considers both the outcome precision of a multiplicity of scenarios and the uncertainty—standard deviation of simulated outcomes—embedded in the predictive fan chart generated for each situation. This multiplicity of scenario results and the predictive fan chart and associated uncertainty provide strong incentives to hedge risks in poverty and income inequality declining via the constant evaluation and revamping of income re-distributive policies; the potential new plans should be flexible and easy to adjust to rapidly changing economic conditions.

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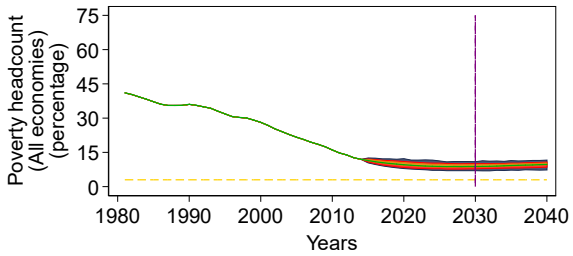
APPENDIX A: GENERAL FIGURES

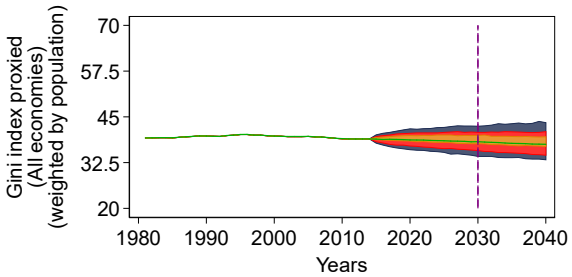
FIGURE A 1. PREDICTED GLOBAL POVERTY HEADCOUNT AND GINI COEFFICIENT

Panel A. Poverty headcount
(Base period: 1980–2014)

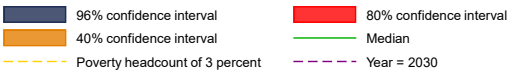


Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 11.42 and 8.84; ii) mean = 11.45 and 8.89; iii) skewness = 0.16 and 0.38; iv) standard deviation = 0.52 and 0.93. Estimated number of persons living in extreme poverty corresponding to the median headcount = 811 and 724 million people.

Panel B. Gini coefficient
(Base period: 1980–2014)



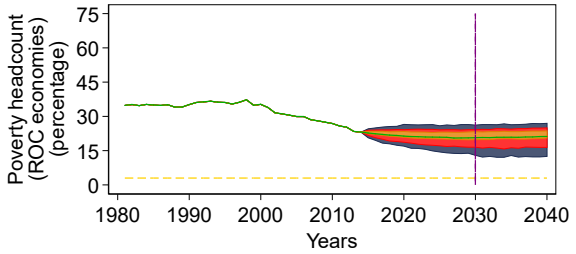
Aggregated Gini index stats derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 38.92 and 38.21; ii) mean = 38.93 and 38.23; iii) skewness = 0.23 and 0.16; iv) standard deviation = 0.55 and 1.99.



Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates.

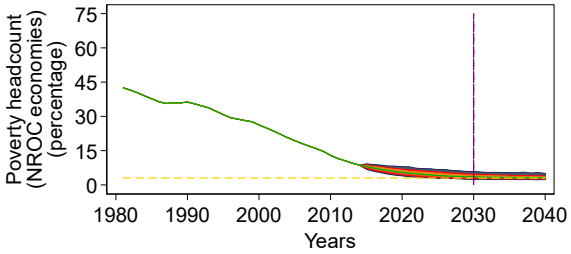
FIGURE A 2. PREDICTED POVERTY HEADCOUNT BY COUNTRY RESOURCE ORIENTATION

Panel A. ROCs
(Base period: 1980–2014)

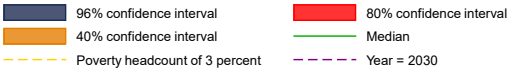


Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 22.73 and 20.68; ii) mean = 22.75 and 20.49; iii) skewness = -0.07 and -0.37; iv) standard deviation = 0.93 and 3.14. Estimated number of persons living in extreme poverty corresponding to the median headcount = 369 and 438 million people.

Panel B. NROCs
(Base period: 1980–2014)



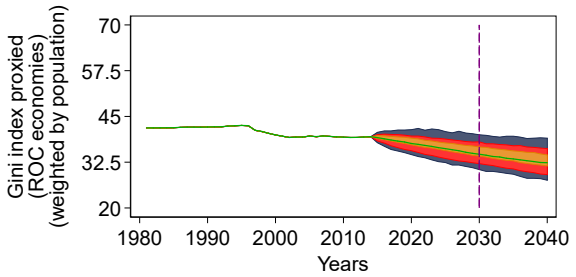
Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 8.03 and 3.53; ii) mean = 8.04 and 3.69; iii) skewness = 0.12 and 2.26; iv) standard deviation = 0.56 and 0.89. Estimated number of persons living in extreme poverty corresponding to the median headcount = 440 and 215 million people.



Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates.

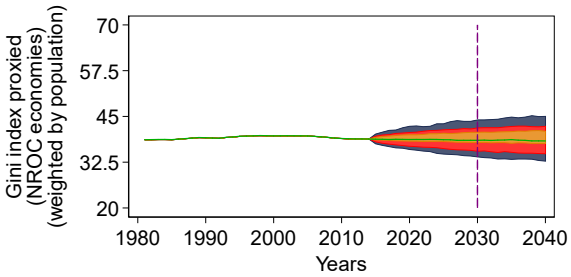
FIGURE A 3. PREDICTED GINI COEFFICIENT BY COUNTRY RESOURCE ORIENTATION

Panel A. ROCs
(Base period: 1980–2014)



Aggregated Gini index stats derived from 500 random draws per year in each of the 46 selected countries. The 2015 and 2030 corresponding results are: i) median = 39.22 and 34.68; ii) mean = 39.20 and 34.87; iii) skewness = 0.04 and 0.43; iv) standard deviation = 0.70 and 2.33.

Panel B. NROCs
(Base period: 1980–2014)

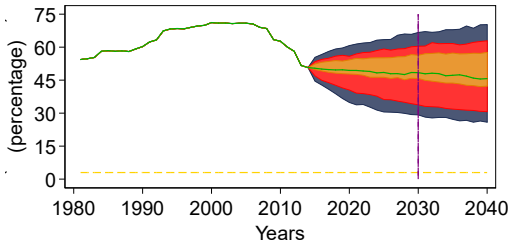


Aggregated Gini index stats derived from 500 random draws per year in each of the 104 selected countries. The 2015 and 2030 corresponding results are: i) median = 38.78 and 38.48; ii) mean = 38.81 and 38.62; iii) skewness = 0.25 and 0.25; iv) standard deviation = 0.61 and 2.45.

Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates.

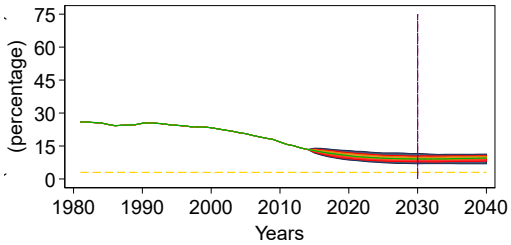
FIGURE A 4. PREDICTED POVERTY HEADCOUNT BY INCOME GROWTH COUNTRY TYPOLOGY

Panel A. LOGCs
(Based period: 1980–2014)



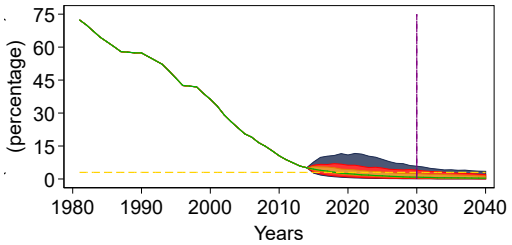
Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 50.44 and 48.41; ii) mean = 50.32 and 47.86; iii) skewness = -0.24 and -0.04; iv) standard deviation = 2.55 and 9.87. Estimated number of persons living in extreme poverty corresponding to the median headcount = 87 and 127 million people.

Panel B. MOGCs
(Based period: 1980–2014)



Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 12.87 and 9.12; ii) mean = 12.89 and 9.15; iii) skewness = 0.04 and 0.33; iv) standard deviation = 0.55 and 1.07. Estimated number of persons living in extreme poverty corresponding to the median headcount = 635 and 531 million people.

Panel C. HOGCs
(Based period: 1980–2014)



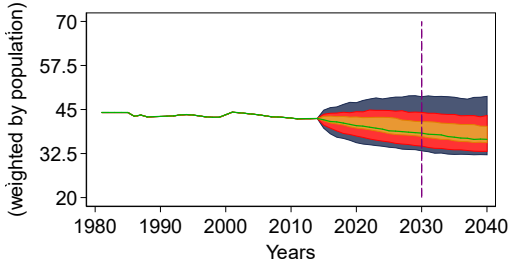
Poverty headcount outcomes derived from 500 random draws per year in each of the 150 selected countries. The 2015 and 2030 corresponding results are: i) median = 4.5 and 0.85; ii) mean = 4.65 and 1.48; iii) skewness = 0.99 and 1.76; iv) standard deviation = 1.30 and 1.59. Estimated number of persons living in extreme poverty corresponding to the median headcount = 90 and 18 million people.

96% confidence interval
80% confidence interval
40% confidence interval
Median
Poverty headcount of 3 percent
Year = 2030

Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates.

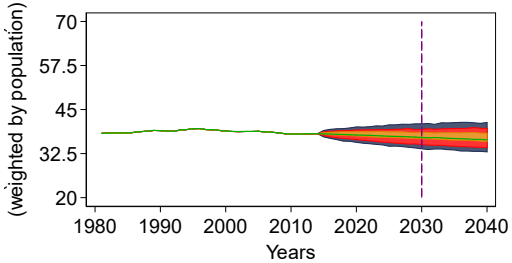
FIGURE A 5. PREDICTED GINI COEFFICIENTS BY INCOME GROWTH COUNTRY TYPOLOGY

Panel A. LOGCs
(Base period: 1980–2014)



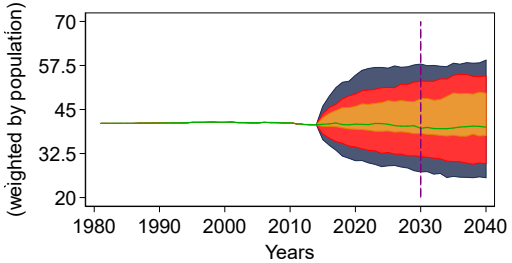
Aggregated Gini index stats derived from 500 random draws per year in each of the 8 selected countries. The 2015 and 2030 corresponding results are: i) median = 42.08 and 38.30; ii) mean = 42.12 and 38.88; iii) skewness = 0.15 and 0.85; iv) standard deviation = 1.23 and 3.73.

Panel B. MOGCs
(Base period: 1980–2014)



Aggregated Gini index stats derived from 500 random draws per year in each of the 117 selected countries. The 2015 and 2030 corresponding results are: i) median = 38.09 and 37.08; ii) mean = 38.11 and 37.20; iii) skewness = 0.15 and 0.41; iv) standard deviation = 0.44 and 1.69.

Panel C. HOGCs
(Base period: 1980–2014)



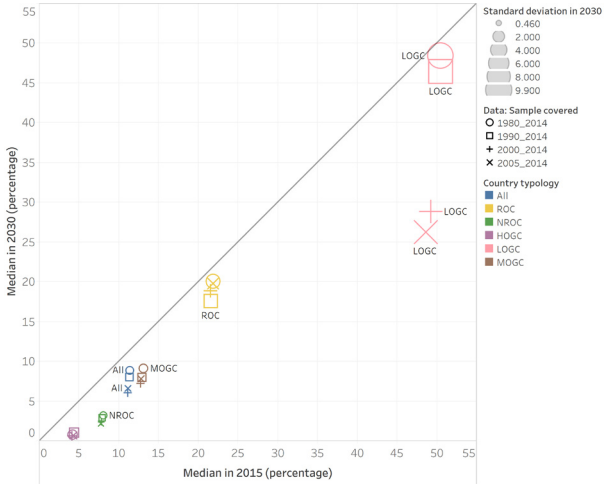
Aggregated Gini index stats derived from 500 random draws per year in each of the 25 selected countries. The 2015 and 2030 corresponding results are: i) median = 40.81 and 39.66; ii) mean = 40.90 and 41.11; iii) skewness = 0.22 and 0.36; iv) standard deviation = 2.27 and 7.90.

96% confidence interval
80% confidence interval
40% confidence interval
Median
Poverty headcount of 3 percent
Year = 2030

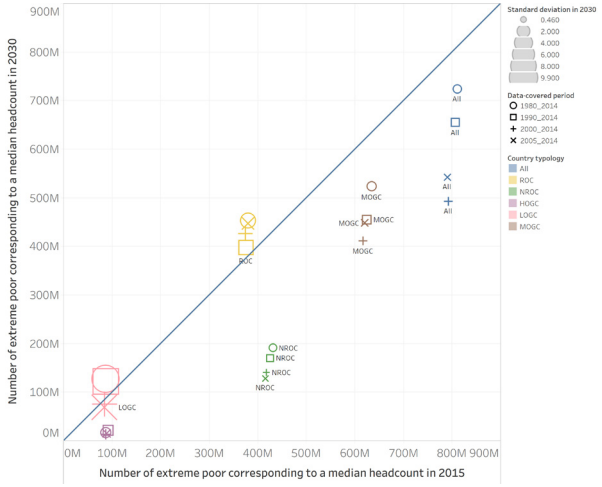
Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates.

FIGURE A 6. SIMULATIONS VARYING THRESHOLD DEFINITIONS OF COUNTRY TYPOLOGIES (TABLE 1) BY MINUS 0.3 PERCENT

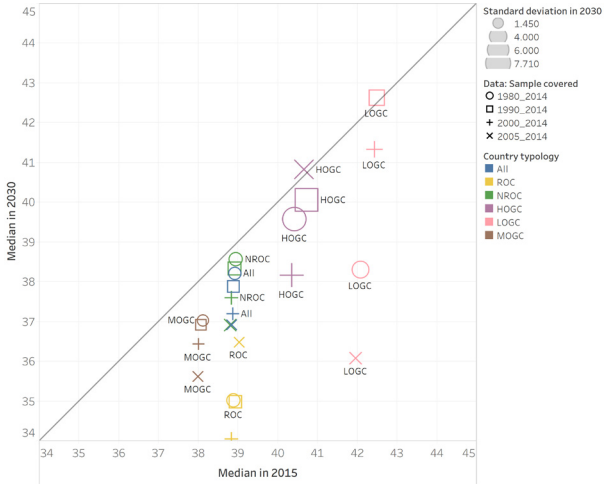
Panel A. Poverty headcount



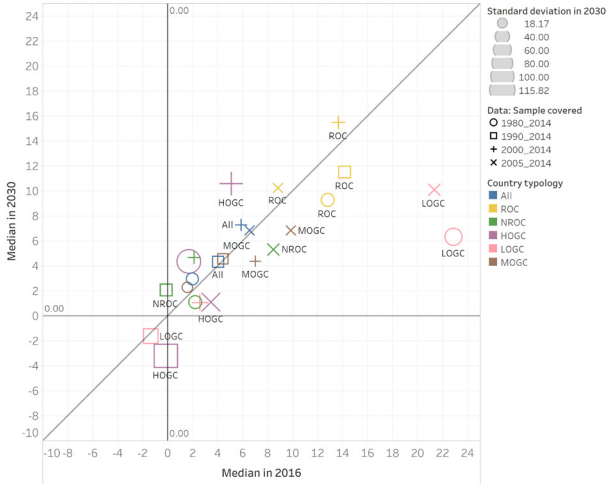
Panel B. Absolute extreme poverty



Panel C. Gini coefficient



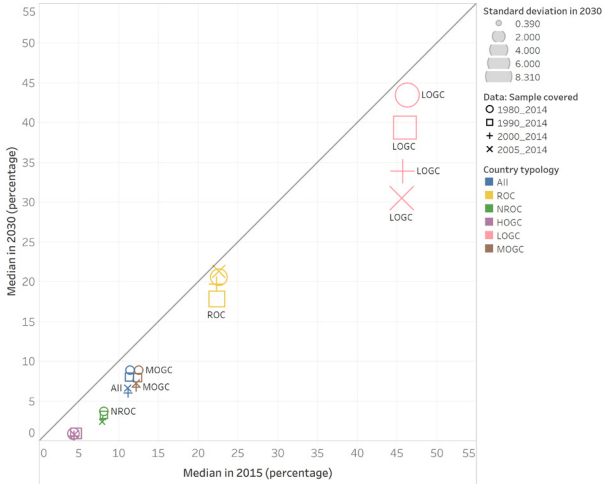
Panel D. B40 – median shared prosperity gap



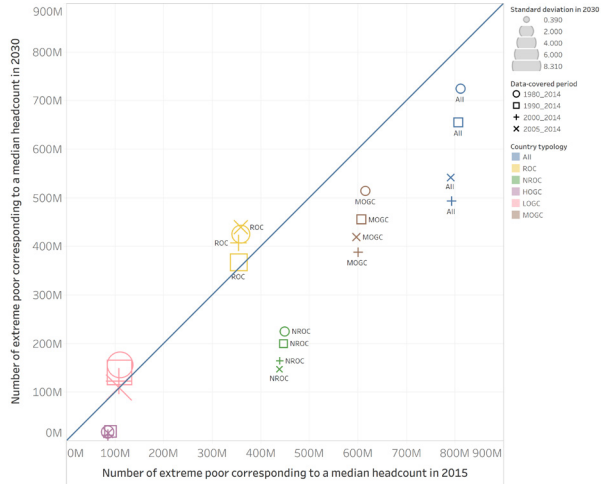
Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditure household survey observations. Projected country population weights the estimates. Five hundred simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014.

FIGURE A 7. SIMULATIONS VARYING THRESHOLD DEFINITIONS OF COUNTRY TYPOLOGIES (TABLE 1) BY PLUS 0.3 PERCENT

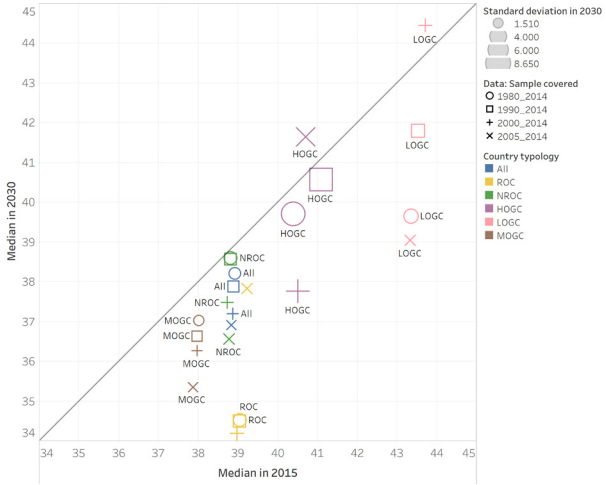
Panel A. Poverty headcount



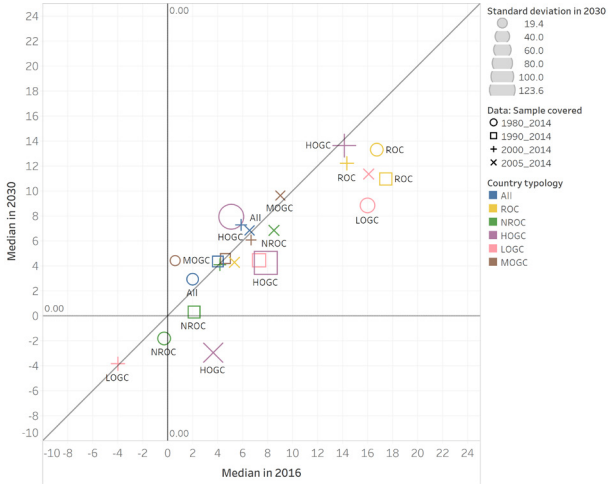
Panel B. Absolute extreme poverty



Panel C. Gini coefficient



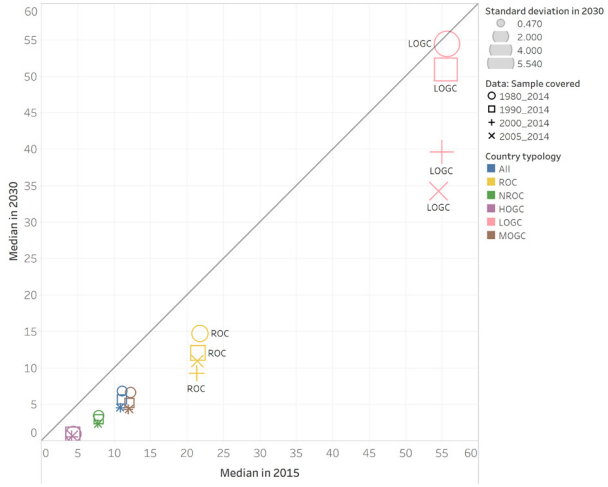
Panel D. B40 – median shared prosperity gap



Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* Per capita consumption growth rates are used to complete the panel of average income/expenditure household survey observations. Projected country population weights the estimates. Five hundred simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014.

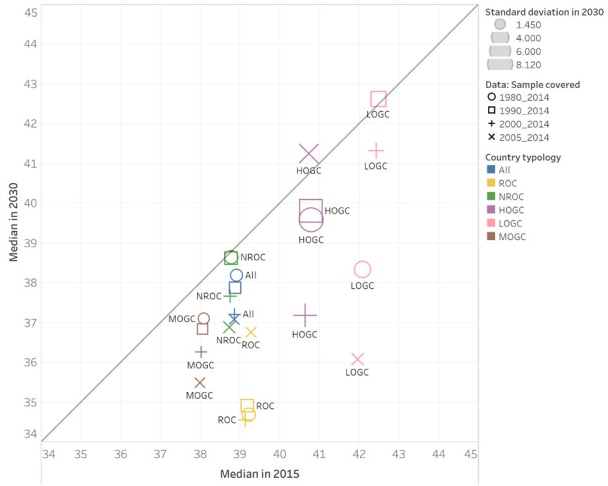
FIGURE A 8. SIMULATIONS BASED ON GDP PER CAPITA GROWTH RATES

Panel A. Poverty headcount

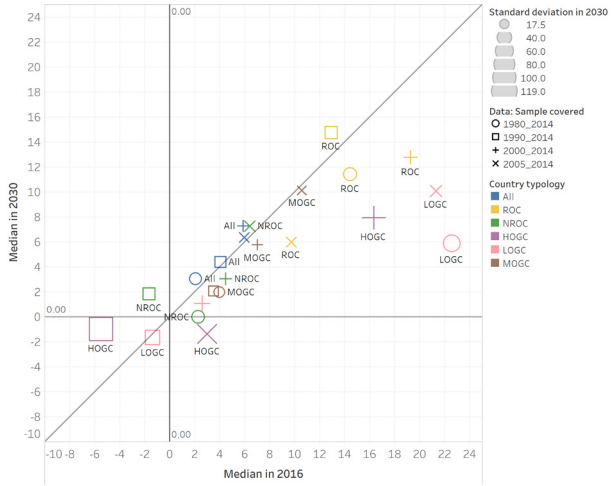


Panel B. Absolute extreme poverty

Panel C. Gini coefficient



Panel D. B40 – median shared prosperity gap



Source: World Development Indicators, PovcalNet, United Nations, Penn World Table 9.0, and the author's calculations. *Note:* GDP per capita growth rates are used to complete the panel of average income/expenditure household survey observations. Projected country population weights the estimates. Five hundred simulations are performed per country and forecasted period. The simulations use 4 sample periods to test for the robustness of results: 1980–2014, 1990–2014, 2000–2014, and 2005–2014.

APPENDIX B: GENERAL TABLES

TABLE B 1. LIST OF COUNTRIES

(1) ID Country	(2) Country	(3) Income Category	(4) Output Growth Category	(5) Resource Category	(6) PovcalNet Number of Surveys
1	Albania	UMC	MOGC	NROC	5
2	Algeria	UMC	MOGC	ROC	3
3	Angola	LMC	MOGC	ROC	2
4	Argentina	HIC	MOGC	NROC	27
5	Armenia	UMC	HOGC	NROC	18
6	Australia	HIC	MOGC	NROC	8
7	Austria	HIC	MOGC	NROC	13
8	Azerbaijan	UMC	HOGC	ROC	6
9	Bangladesh	LMC	MOGC	NROC	9
10	Belarus	UMC	HOGC	NROC	21
11	Belgium	HIC	MOGC	NROC	13
12	Belize	UMC	MOGC	NROC	7
13	Benin	LIC	MOGC	ROC	3
14	Bhutan	LMC	HOGC	NROC	4
15	Bolivia	LMC	MOGC	NROC	19
16	Bosnia and Herzegovina	UMC	HOGC	NROC	5
17	Botswana	UMC	HOGC	NROC	4
18	Brazil	UMC	MOGC	NROC	31
19	Bulgaria	UMC	HOGC	NROC	16
20	Burkina Faso	LIC	MOGC	ROC	5
21	Burundi	LIC	MOGC	ROC	4
22	Cabo Verde	LMC	MOGC	NROC	2
23	Cameroon	LMC	MOGC	ROC	4
24	Canada	HIC	MOGC	NROC	11
25	Central African Republic	LIC	MOGC	ROC	3
26	Chad	LIC	MOGC	ROC	2
27	Chile	HIC	HOGC	ROC	13
28	China	UMC	HOGC	NROC	16
29	Colombia	UMC	MOGC	NROC	18
30	Comoros	LIC	MOGC	NROC	2
31	Congo, Dem. Rep.	LIC	LOGC	ROC	2
32	Congo, Rep.	LMC	MOGC	ROC	2
33	Costa Rica	UMC	MOGC	NROC	30
34	Croatia	HIC	MOGC	NROC	14
35	Cyprus	HIC	MOGC	NROC	12
36	Czech Republic	HIC	MOGC	NROC	14
37	Côte d'Ivoire	LMC	LOGC	NROC	10
38	Denmark	HIC	MOGC	NROC	13
39	Djibouti	LMC	LOGC	NROC	3
40	Dominican Republic	UMC	MOGC	NROC	22
41	Ecuador	UMC	MOGC	ROC	20
42	Egypt, Arab Rep.	LMC	MOGC	ROC	8
43	El Salvador	LMC	MOGC	NROC	23
44	Estonia	HIC	HOGC	NROC	19
45	Ethiopia	LIC	MOGC	ROC	6
46	Fiji	UMC	MOGC	NROC	3
47	Finland	HIC	MOGC	NROC	13
48	France	HIC	MOGC	NROC	13
49	Gabon	UMC	MOGC	ROC	2

(1) ID Country	(2) Country	(3) Income Category	(4) Output Growth Category	(5) Resource Category	(6) PovcalNet Number of Surveys
50	Gambia, The	LIC	LOGC	NROC	4
51	Georgia	LMC	HOGC	NROC	21
52	Germany	HIC	MOGC	NROC	11
53	Ghana	LMC	MOGC	ROC	6
54	Greece	HIC	MOGC	NROC	13
55	Guatemala	UMC	MOGC	NROC	6
56	Guinea	LIC	MOGC	ROC	5
57	Guinea-Bissau	LIC	MOGC	ROC	4
58	Haiti	LIC	LOGC	NROC	2
59	Honduras	LMC	MOGC	NROC	28
60	Hungary	HIC	MOGC	NROC	21
61	Iceland	HIC	MOGC	NROC	12
62	India	LMC	MOGC	NROC	6
63	Indonesia	LMC	HOGC	ROC	25
64	Iran, Islamic Rep.	UMC	MOGC	ROC	9
65	Iraq	UMC	MOGC	ROC	2
66	Ireland	HIC	MOGC	NROC	13
67	Israel	HIC	MOGC	NROC	8
68	Italy	HIC	MOGC	NROC	13
69	Jamaica	UMC	MOGC	NROC	7
70	Japan	HIC	MOGC	NROC	1
71	Jordan	UMC	MOGC	NROC	7
72	Kazakhstan	UMC	MOGC	ROC	17
73	Kenya	LMC	MOGC	NROC	5
74	Korea, Rep.	HIC	HOGC	NROC	4
75	Kyrgyz Republic	LMC	MOGC	NROC	18
76	Lao PDR	LMC	HOGC	ROC	5
77	Latvia	HIC	HOGC	NROC	19
78	Lebanon	UMC	MOGC	NROC	1
79	Lesotho	LMC	MOGC	NROC	4
80	Liberia	LIC	MOGC	ROC	2
81	Lithuania	HIC	HOGC	NROC	20
82	Luxembourg	HIC	MOGC	NROC	13
83	Macedonia, FYR	UMC	MOGC	NROC	14
84	Madagascar	LIC	LOGC	NROC	7
85	Malawi	LIC	MOGC	ROC	3
86	Malaysia	UMC	HOGC	ROC	12
87	Maldives	UMC	HOGC	NROC	2
88	Mali	LIC	MOGC	NROC	4
89	Malta	HIC	MOGC	NROC	10
90	Mauritania	LMC	MOGC	ROC	7
91	Mauritius	UMC	MOGC	NROC	2
92	Mexico	UMC	MOGC	NROC	16
93	Moldova	LMC	MOGC	NROC	20
94	Mongolia	LMC	MOGC	ROC	9
95	Montenegro	UMC	MOGC	NROC	10
96	Morocco	LMC	MOGC	NROC	6
97	Mozambique	LIC	MOGC	ROC	4
98	Myanmar	LMC	HOGC	ROC	1
99	Namibia	UMC	MOGC	NROC	4
100	Nepal	LIC	MOGC	NROC	4
101	Netherlands	HIC	MOGC	NROC	12
102	Nicaragua	LMC	MOGC	NROC	6
103	Niger	LIC	LOGC	NROC	6
104	Nigeria	LMC	MOGC	ROC	5
105	Norway	HIC	MOGC	NROC	13
106	Pakistan	LMC	MOGC	NROC	12
107	Panama	HIC	MOGC	NROC	23

(1) ID Country	(2) Country	(3) Income Category	(4) Output Growth Category	(5) Resource Category	(6) PovcalNet Number of Surveys
108	Paraguay	UMC	MOGC	NROC	20
109	Peru	UMC	MOGC	NROC	22
110	Philippines	LMC	MOGC	NROC	11
111	Poland	HIC	MOGC	NROC	24
112	Portugal	HIC	MOGC	NROC	13
113	Romania	UMC	HOGC	NROC	22
114	Russian Federation	UMC	MOGC	ROC	21
115	Rwanda	LIC	MOGC	ROC	5
116	Senegal	LIC	MOGC	NROC	5
117	Serbia	UMC	MOGC	NROC	13
118	Seychelles	HIC	HOGC	NROC	3
119	Sierra Leone	LIC	MOGC	ROC	3
120	Slovak Republic	HIC	HOGC	NROC	13
121	Slovenia	HIC	MOGC	NROC	16
122	South Africa	UMC	MOGC	NROC	7
123	Spain	HIC	MOGC	NROC	13
124	Sri Lanka	LMC	MOGC	NROC	8
125	St. Lucia	UMC	MOGC	NROC	1
126	Suriname	UMC	MOGC	ROC	1
127	Swaziland	LMC	MOGC	NROC	3
128	Sweden	HIC	MOGC	NROC	13
129	Switzerland	HIC	MOGC	NROC	10
130	Syrian Arab Republic	LIC	MOGC	ROC	1
131	São Tomé and Principe	LMC	MOGC	NROC	2
132	Tajikistan	LIC	HOGC	NROC	6
133	Tanzania	LIC	MOGC	ROC	4
134	Thailand	UMC	MOGC	NROC	21
135	Togo	LIC	MOGC	ROC	3
136	Trinidad and Tobago	HIC	MOGC	ROC	2
137	Tunisia	LMC	MOGC	NROC	6
138	Turkey	UMC	MOGC	NROC	17
139	Turkmenistan	UMC	HOGC	ROC	1
140	Uganda	LIC	MOGC	ROC	9
141	Ukraine	LMC	MOGC	NROC	20
142	United Kingdom	HIC	MOGC	NROC	12
143	United States	HIC	MOGC	NROC	10
144	Uruguay	HIC	MOGC	NROC	24
145	Uzbekistan	LMC	MOGC	ROC	4
146	Venezuela, RB	UMC	MOGC	ROC	13
147	Vietnam	LMC	HOGC	NROC	10
148	Yemen, Rep.	LIC	MOGC	ROC	3
149	Zambia	LMC	MOGC	ROC	9
150	Zimbabwe	LIC	LOGC	NROC	1

Source: Penn World Table 9.0, World Development Indicators, PovcalNet, United Nations, and the author's calculations. *Note:* ROCs denotes resource-output oriented countries. NROCs symbolizes non-resource-output oriented countries. LOGCs stands for low-output growth countries. MOGCs depicts middle-output growth countries. HOGCs refers to high-output growth countries. Table 1 provides details of the definitions of the country classifications.

TABLE B 2. DESCRIPTIVE STATISTICS

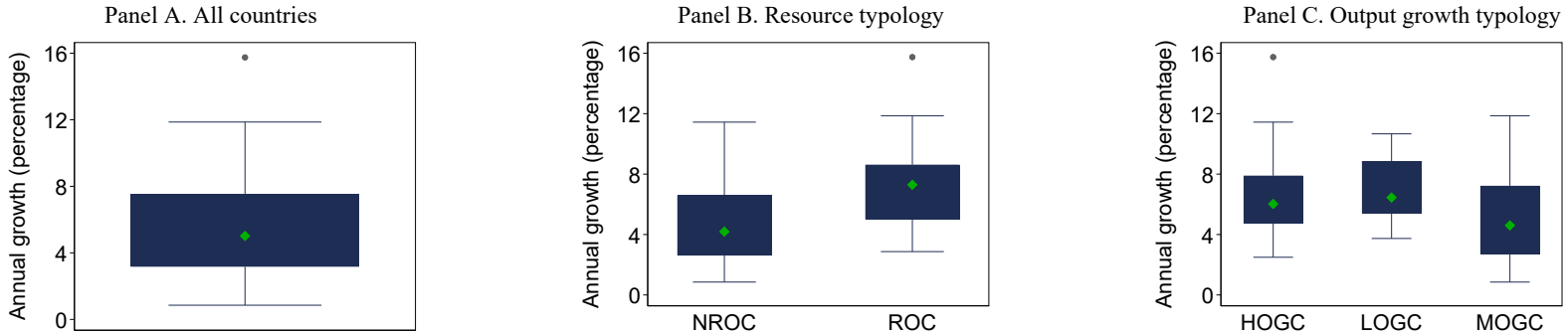
	(1) Annual observations	(2) Mean	(3) Standard deviation	(4) Minimum	(5) Maximum	(6) Coefficient of variation
All countries						
GDP per capita, 2011 PPP U.S. dollars	4,892	11,423	12,465	162	84,362	1.1
GDP per capita, annual growth (percent)	4,892	1.7%	5.2%	-57.5%	32.0%	3.1
Per capita consumption, 2011 PPP U.S. dollars	4,892	8,631	8,584	120	42,758	1.0
Per capita consumption, annual growth (percent)	4,892	1.6%	5.9%	-26.3%	24.7%	3.7
Mean income, 2011 PPP U.S. dollars/month	1,383	533	498	23	2,218	0.9
Mean income, average annual growth (percent)	1,200	1.8%	8.8%	-68.8%	58.0%	4.8
Gini index	1,339	39	10	16	66	0.2
Gini index, average annual growth (percent)	1,195	-0.3%	4.8%	-74.2%	29.8%	-18.4
ROCs						
GDP per capita, 2011 PPP U.S. dollars	1,486	5,511	5,840	162	31,598	1.1
GDP per capita, annual growth (percent)	1,486	1.4%	6.0%	-42.9%	30.2%	4.3
Per capita consumption, 2011 PPP U.S. dollars	1,486	3,741	3,674	120	22,488	1.0
Per capita consumption, annual growth (percent)	1,486	1.2%	7.3%	-25.4%	23.5%	6.3
Mean income, 2011 PPP U.S. dollars/month	258	215	171	23	756	0.8
Mean income, average annual growth (percent)	197	2.2%	7.4%	-26.2%	43.6%	3.3
Gini index	235	42	8	16	66	0.2
Gini index, average annual growth (percent)	193	-1.0%	7.0%	-74.2%	22.2%	-6.9
NROCs						
GDP per capita, 2011 PPP U.S. dollars	3,406	14,003	13,653	727	84,362	1.0
GDP per capita, annual growth (percent)	3,406	1.8%	4.7%	-57.5%	32.0%	2.7
Per capita consumption, 2011 PPP U.S. dollars	3,406	10,765	9,217	452	42,758	0.9
Per capita consumption, annual growth (percent)	3,406	1.8%	5.2%	-26.3%	24.7%	2.9
Mean income, 2011 PPP U.S. dollars/month	1,125	606	519	35	2,218	0.9
Mean income, average annual growth (percent)	1,003	1.8%	9.1%	-68.8%	58.0%	5.2
Gini index	1,104	39	10	21	65	0.3
Gini index, average annual growth (percent)	1,002	-0.1%	4.3%	-21.9%	29.8%	-35.8
LOGCs						
GDP per capita, 2011 PPP U.S. dollars	271	1,681	676	555	3,693	0.4
GDP per capita, annual growth (percent)	271	-0.8%	4.6%	-21.3%	13.2%	-5.6
Per capita consumption, 2011 PPP U.S. dollars	271	1,462	574	511	3,043	0.4
Per capita consumption, annual growth (percent)	271	-0.4%	7.3%	-21.9%	21.0%	-18.4
Mean income, 2011 PPP U.S. dollars/month	32	102	59	23	267	0.6
Mean income, average annual growth (percent)	24	-2.2%	7.4%	-23.5%	8.6%	-3.3
Gini index	32	42	6	31	61	0.1
Gini index, average annual growth (percent)	24	-0.8%	5.7%	-18.2%	10.3%	-7.2
MOGCs						
GDP per capita, 2011 PPP U.S. dollars	3,886	12,496	13,384	162	84,362	1.1
GDP per capita, annual growth (percent)	3,886	1.4%	4.6%	-46.5%	30.2%	3.2
Per capita consumption, 2011 PPP U.S. dollars	3,886	9,409	9,114	120	42,758	1.0
Per capita consumption, annual growth (percent)	3,886	1.4%	5.6%	-25.2%	23.6%	4.1
Mean income, 2011 PPP U.S. dollars/month	1,089	594	533	24	2,218	0.9
Mean income, average annual growth (percent)	966	1.6%	8.4%	-68.8%	58.0%	5.3
Gini index	1,079	40	10	21	66	0.3
Gini index, average annual growth (percent)	966	-0.3%	4.0%	-27.6%	22.2%	-15.3
HOGCs						
GDP per capita, 2011 PPP U.S. dollars	735	9,341	6,443	742	34,326	0.7
GDP per capita, annual growth (percent)	735	3.6%	7.1%	-57.5%	32.0%	1.9
Per capita consumption, 2011 PPP U.S. dollars	735	7,160	5,182	452	22,146	0.7
Per capita consumption, annual growth (percent)	735	3.5%	6.8%	-26.3%	24.7%	1.9
Mean income, 2011 PPP U.S. dollars/month	262	335	221	35	1,182	0.7
Mean income, average annual growth (percent)	210	3.5%	10.5%	-42.4%	34.7%	3.0
Gini index	228	35	8	16	65	0.2
Gini index, average annual growth (percent)	205	-0.2%	7.5%	-74.2%	29.8%	-39.5

Source: Penn World Table 9.0, World Development Indicators, World Bank PovcalNet, United Nations, and the author's estimates. *Note:* GDP per capita estimates are in PPP 2011 U.S. dollars. Information over the period 1980–2014. Annual growth rates of the Gini index are calculated as the average between spells.

APPENDIX C: VARIANCE OF MEAN INCOME GROWTH

The standard deviation of mean income growth is presented in Figure C 1, Appendix C. This country-specific variability in ROCs is generally higher than that faced by NROC economies (Figure C 1, Panel B, Appendix C). In terms of their median, LOGCs present larger standard deviations of mean income growth than HOGCs and MOGCs, with MOGCs representing the economies with the smallest median value (Figure C 1, Panel C, Appendix C). Furthermore, via a standard variance decomposition of the OLS estimates of Equation (1), we identified three main features of the dispersion of the growth in the mean income (Figure C 2 in Appendix C). First, idiosyncratic factors drive the variability in income growth faced by all countries and country typologies.[37] Second, global factors affecting income growth appear to be less relevant in ROCs and LOGCs. Third, the covariance component between the growth of global income per capita and global commodity prices is negligible, $cov[g_t, p_t] \approx 0$, over the period 1980–2014 and across countries.

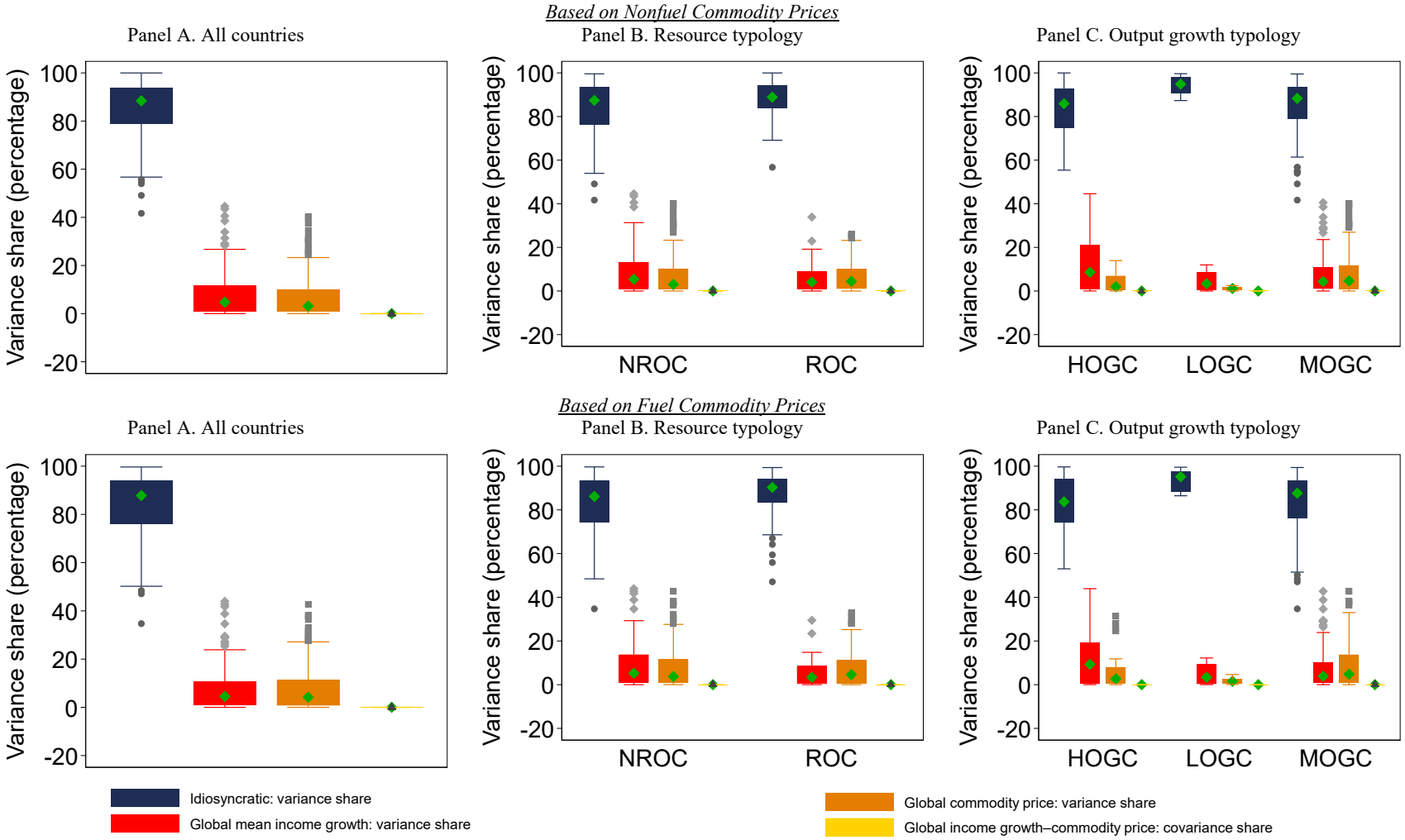
FIGURE C 1. VARIABILITY OF MEAN INCOME GROWTH



Source: Penn World Table 9.0, World Development Indicators, United Nations, and the author's estimates. *Note:* Variability measured by the standard deviation of mean income growth. Country regressions over the period 1980–2014. Similar results are obtained using the following periods instead: 1990–2014, 2000–2014, and 2005–2014. The total number of countries used in this estimation is 150. The number of NROC and ROC economies is 104 and 46, respectively. The number of countries in the classification LOGCs, MOGCs, and HOGCs are 8, 117, and 25, respectively.

[37] Despite the inclusion of two global factors affecting mean income growth, the model in Equation (1) does not disaggregate the idiosyncratic components affecting the country performance of growth of mean income. Besides, note that all the idiosyncratic random forces are captured via the error term in Equation (1). This error term, however, could include omitted global components as well.

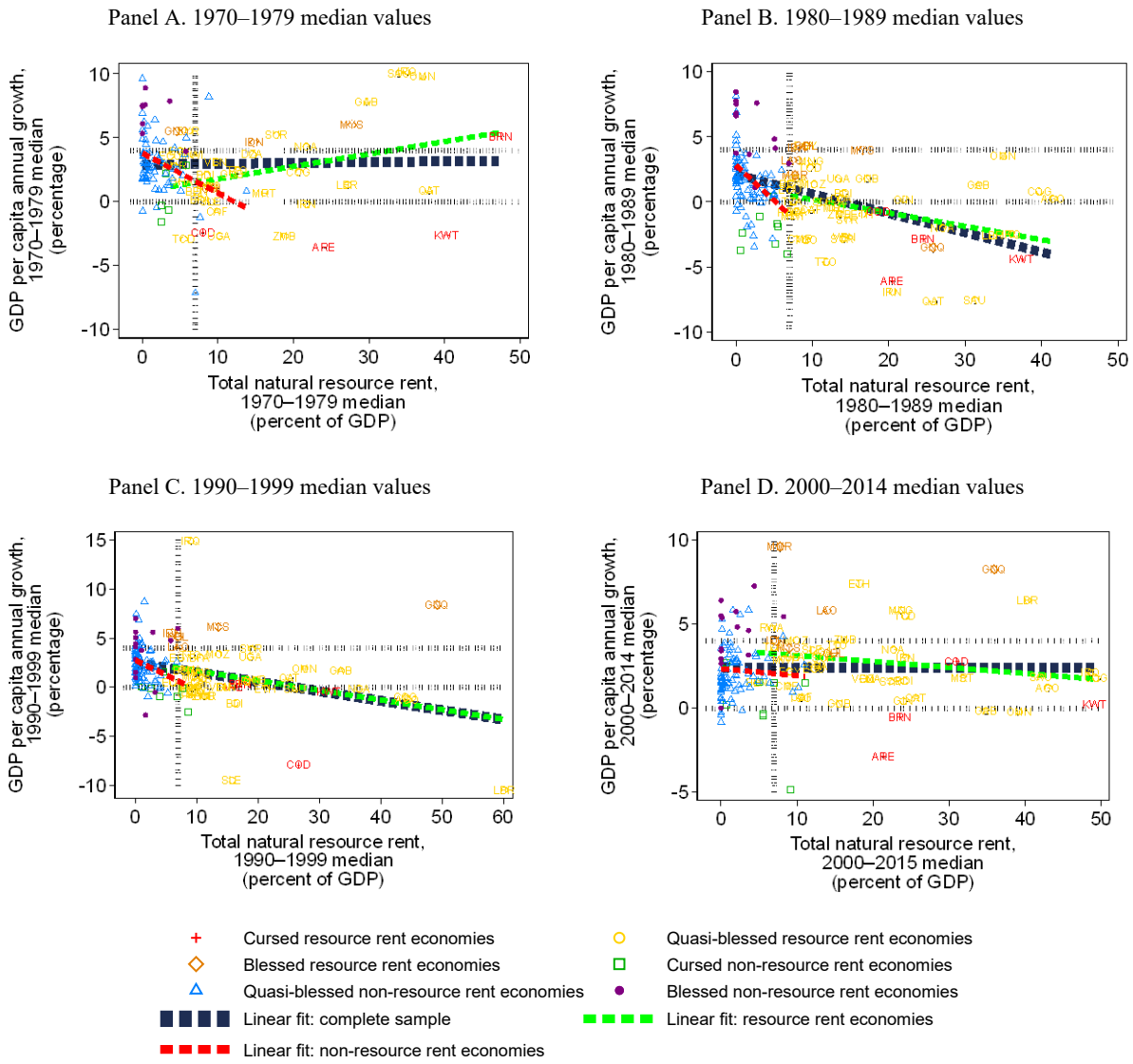
FIGURE C 2. STANDARD VARIANCE DECOMPOSITION OF MEAN INCOME GROWTH



Source: Penn World Table 9.0, World Development Indicators, United Nations, and the author's estimates. *Note:* Variability is measured by the standard deviation of mean income growth. All panels consider country regression information over the period 1980–2014. Similar results are obtained using the following periods instead: 1990–2014, 2000–2014, and 2005–2014. The total number of countries used in this estimation is 150. The number of NROC and ROC economies is 104 and 46, respectively. The number of countries in the classifications LOGCs, MOGCs, and HOGCs are 8, 117, and 25, respectively.

APPENDIX D: SOME STYLIZED FACTS OF THE RESOURCE TYPOLOGY

FIGURE D 1. GDP PER CAPITA GROWTH AND NATURAL RESOURCE RENTS VARYING ACROSS DECADES

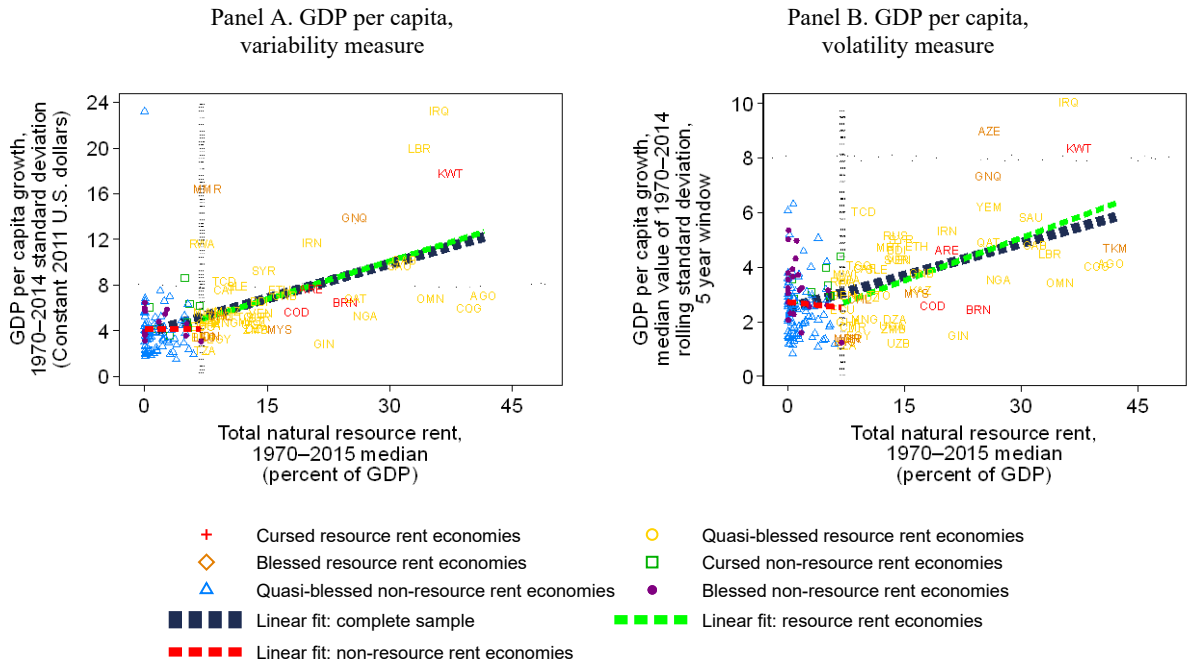


Source: Penn World Table 9.0, World Development Indicators, United Nations, and the author's estimates. *Note:* GDP per capita is in PPP 2011 U.S. dollars. The sample includes 148 countries, each with more than 44 annual observations of GDP per capita over the period 1970–2014.

To determine the strength of the median values and trends presented in Figure 1, we check the relationship between GDP per capita growth and natural resource rents over decades (Figure D 1 in Appendix D). In the 1970s, in all our sample of economies, we find a flat association between output per capita growth and resource rents. However, this overall association—the blue dotted

line—becomes negative in the 1980s and 1990s then reverts to a flattened association in the 2000s. Over the decades, this association appears to be driven by the performance of resource-based countries. ROCs show a positive association—the green dotted line—in the 1970s; this association reverses to become negative in the subsequent decades. In contrast, in the NROCs, there is an unchanging negative association between GDP per capita growth and natural resource rents across the decades—the red-dotted line.

FIGURE D 2. OUTPUT VARIABILITY AND NATURAL RESOURCE RENTS



Source: Penn World Table 9.0, World Development Indicators, United Nations, and the author's estimates. *Note:* GDP per capita is in PPP 2011 U.S. dollars. The sample includes 148 countries, each with more than 44 annual observations of GDP per capita over the period 1970–2014.

We also investigate the performance of the variability and volatility of GDP per capita growth according to their level of resource rents across countries. Panels A and B of Figure D 2 in Appendix D show that ROCs present higher variability and volatility of average output per capita growth. In contrast, this association is almost negligible in NROC economies.