A Bayesian Reappraisal of the Inequality–Growth Relationship

Subaran Roy*& Keshav Sethi†

Abstract

According to the existing literature, inequality may have a positive, negative, or no association with economic growth. There is still no clear consensus regarding the relationship between inequality and growth making this an active area of research. This study makes an attempt to decipher the impact of inequality on growth and address the issue of model uncertainty utilizing pertinent data on inequality for 56 countries for the time period 1999-2020. First, we document significant stylized facts between inequality and growth and then apply Bayesian Moving Average (BMA) method to examine whether inequality matters in the presence of major growth determinants. Our results indicate inequality *does* matter in the process of growth. Specifically, we find that inequality has an adverse impact on growth. The Posterior Inclusion Probability (PIP) of inequality greater than 0.70 across all models confirms the negative impact of inequality on growth. Our results withstand various robustness checks.

Keywords: Inequality, Economic Growth, Model Uncertainty, Bayesian Moving Averaging

JEL Classification: 040, C5, 047, C6

*Professor of Economics. Jindal School of Government and Public Policy, JGU. Email: subaran@jgu.edu.in

†PhD scholar at Jindal School of Government and Public Policy, JGU. Email: ksethi@jgu.edu.in

1 Introduction

Economic inequality around the world today is primarily a consequence of the unequal progress of countries over the last two centuries. It is clear that certain countries grew at a faster rate while others lagged, resulting in an increase in per capita income disparities over time across. In the 1950s and 1960s, economists such as Nicholas Kaldor and Simon Kuznets contended that there is a trade-off between eliminating inequality and encouraging growth. During the postwar period, many East Asian economies had relatively low levels of equality (for countries with comparable income levels) and grew at unprecedented rates. In stark contrast to this experience, many Latin American countries enjoyed substantially better levels of equality and expanded at a fraction of the typical East Asian rate. These patterns sparked renewed attention in the relationship between inequality and growth, particularly a rethinking of how a country's degree of income inequality predicts its future rate of economic growth.

In this paper, we make an attempt to clarify the relationship between income inequality and economic growth from 1999 to 2020 for a set of 56 countries using Bayesian Model Averaging (BMA) method. We focus on income inequality between countries and incorporate relevant growth determinants in from World Development Indicators (WDI) data set.[1] We utilize World Bank Database for countries for which the Gini index is available from 1999 to 2020 and the corresponding GDP per capita (constant 2015 US$). We have selected the period 1999–2020 for two key reasons. First, this timeframe ensures the availability of consistent data for both the dependent and independent variables required for our analysis, particularly the Gini coefficient, while also maximizing the number of countries included in the study. Second, this period aligns with significant global development initiatives introduced after 1999, notably the Millennium Development Goals (MDGs) and

[1] We are using Gini coefficient in our study as it is a well tested and proved measure of income inequality, widely used in the exiting literature.The method is described in the estimation strategy section.

Sustainable Development Goals (SDGs). The MDGs, launched in 2000, aimed to reduce global poverty and promote sustainable development, laying the foundation for addressing inequality across nations. Building on this, the SDGs, introduced in 2015, reinforced these efforts, with Goal 10 specifically dedicated to reducing inequality within and among countries. Thus, focusing on this period will help us in better policy-designing.

The contributions of this paper include the fact that we are taking a perspective by examining the relationship between income inequality and economic growth for a diverse set of 56 countries from 1999 to 2020 and not restricting the analysis to a specific geographic region or any particular income group. Secondly, this paper incorporates a comprehensive range of potential determinants that could affect the relationship between income inequality and economic growth. We investigate how various growth-promoting factors influence the inequality-growth nexus. Most importantly, we address the model uncertainty in the existing literature regarding the inclusion of different sets of explanatory variables in growth inequality relationship. Studies in the existing scholarship have addressed this issue, but primarily in the context of the relationship between economic growth and other variables such as public investment, R&D, and others (e.g., Fernandez et al., 2001; Sala-I-Martin, 1997; Durlauf et al., 2005; Arin and Braunfels, 2017; Arin et al., 2019; Horvath, 2011; Eris and Ulasan, 2013; Man, 2015; Hasan et al., 2016). We use the Bayesian Model Averaging (BMA) method that allows for the consideration of model uncertainty (i.e., the choice of determinants can significantly impact the results) and also provides a more reliable identification of the key determinants affecting the relationship between income inequality and economic growth. BMA enables us to manage model uncertainty by averaging over possible combinations of models rather than selecting a single best-fit model, providing a more robust set of determinants (e.g., Hinne et al., 2020; Hoeting et al., 1999; Fragoso and Neto, 2015). BMA fundamentally starts with uncertainty across models, and then Bayesian updating of beliefs is applied according to observations. This methodological approach and our analysis contribute significant insights to the ongoing debate in the economic literature regarding the interplay between growth and inequality.

The impact of income inequality on economic growth have been the subject of interest and debate among economists for more than 60 years. The main question for this debate is does income inequality tend to improve, worsen or have no significant effect on economic growth? This started with Kuznets (1954) inverted U-hypothesis, in which he argued that inequality tends to rise in a country's early stages of economic development and observed that it then appears to stabilize and decline as developed economies continue to grow and mature giving rise to what is now known as the Kuznets curve. However, this hypothesis was challenged in the existing literature for sample selection bias.[2] Later, based on different country groups and growth determinants, a number of studies reported that income inequality might be either positively or negatively related to economic growth. In addition, several studies have yielded inconclusive findings, with most reporting that the relationship is positive in high-income and negative in low-income countries. A few studies have also reported no significant relationship between inequality and growth.

Given such theoretical ambiguity, it is not surprising that empirical findings on the relationship between income disparity and economic growth continue to be contested. It is commonly believed that income inequality reduces economic growth across countries as it fuels social dissatisfaction and raises the threat of social, political, and economic unrest in the country. This negative relationship has been confirmed by numerous empirical findings.[3] However, studies that found a positive correlation between inequality and growth have cast doubt on the evidence of

[2]Saith (1983), Ahluwalia (1976) and Fields (1991) argued that Kuznets (1955) did not hypothesize about the income of low developed countries (LDC), as a result the inverted U hypothesis does not work for LDCs. They showed that the relationship between income inequality and economic growth seem to be associated with the "patterns of growth" i.e., specific characteristics of a country such as social structure, political system, and natural resources. Hence, countries with similar characteristics exhibits a common inequality-growth relationship.

[3]See Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996) and Panniza (2002).

a negative association. These results are operational in the light of various transmission mechanisms (or channels) linking income inequality to economic growth. These include, technological advancements, savings rate, institutions, fertility rate, imperfection of credit markets and investment climate (e.g., trade, FDI etc.).[4]

The existing literature explaining the positive relationship explains the pathways through which distribution of income might affect the economic growth. For e.g, income inequality exerts a positive influence on economic growth through saving rate. As total income in the economy increases, so do people's savings. In the presence of high income inequality, rich people earn high incomes which help them to save more, thereby enhancing aggregate savings and economic growth in the long run.[5] However, depending on the circumstances of the country, the consequences of some channels can be either favorable or negative. For e.g., Early stages of technology innovations favor technically trained workers over unskilled workers. High income inequality will rise as a result of the formation of a wage gap between skilled and unskilled workers in the economy, increasing unemployment in the country.[6] On the other hand, as the economy progresses to more mature stages of technological development, income inequality decreases. This is due to the fact as more labor shifts to the sector using new technology, the incomes of those who remained in the sector with old technology, rise due to the scarcity of labor in that sector. As a consequence, the wage discrepancy between them narrows, reducing income inequality.[7]

The present literature also includes studies that seek to explain both the positive and negative relationships between inequality and growth. Halter et al. (2014) found that higher inequality helps economic performance in the short term but reduces economic growth in the long run. The growth-promoting effects arise in short run from purely economic processes (convex saving functions, capital market

[4]See Partridge (1997), Li and Zou (1998), Forbes (2000), Rangel et al. (2002) and Westhuizen (2008).

[5]See Corneo and Jeanne (2001) and Peng (2008).

[6]See Krueger (1993) and Aghion et al. (1999).

[7]See Galor and Tsiddon (1997) and Helpman (1997).

imperfections, innovation and incentives) while the growth-reducing effects in long run, involve the political process, the change of institutions, the rise of sociopolitical movements, or they operate through changes in the educational attainment of the population. Similarly, Voitchovsky (2005) found that inequality at the top end of the distribution is positively associated with growth, while inequality lower down the distribution is negatively related to subsequent growth. Although, there exists vibrant literature available explaining the link between inequality and growth yet there is no unanimity on the much debated issue.

The rest of the paper is organized as follows. Section II describes our data and descriptive findings of the study. Section III is covering the estimation technique used in the study. Section IV presents our empirical results and inferences drawn and Section V concludes.

2 Data & Stylized Facts

The World Development Indicators (WDI) database provided information on the Gini coefficient for 56 countries for the time period 1999 - 2020. Data on GDP (constant 2015 US$), GDP per capita (constant 2015 US$), and growth determinants (or control variables) have also been used from WDI.[8] Using the GDP per capita series, average annual growth rates from 1999 to 2020 are calculated.

Tables 1 and 2 compare the top ten countries' income shares to the bottom ten countries' income shares in 1999 (Table 1) and 2020 (Table 2). We find that share of the bottom 10 countries has increased but not significantly during the period 1999 to 2020. The share of the bottom 10 countries' marginally increased by less than 1% during this period. The top ten countries' income shares remained very steady, with 50.8% in 1999 and 48.4% in 2020. In the list of the top 10 countries UK is replaced by Finland in 2020. On the other hand, El Salvador and Ecuador join the

[8]A list of all other variables used in the study is provided in the appendix section.

bottom 10 countries list in 2020 replacing China and Belarus from the 1999 list.[9] Thus, in terms of share of income there has been no significant improvement in the inequality landscape.

Table 1: Income share of top and bottom ten country groups in 1999

Countries	GDP_pc (1999)	% Share (1999)	Group
Luxembourg	87695.34	50.85%	Top 10 countries
Switzerland	71583.69		
Norway	65768.99		
Denmark	47622.44		
United States	47360.54		
Iceland	40725.89		
Sweden	39309.60		
Netherlands	39106.39		
Ireland	38557.45		
United Kingdom	37975.10		
Belarus	2461.83	1.58%	Bottom 10 countries
Bolivia	2048.03		
China	2038.20		
Indonesia	1804.71		
Honduras	1714.96		
Georgia	1508.66		
Ukraine	1327.57		
Moldova	1307.98		
Armenia	1210.36		
Kyrgyz Republic	689.42		

[9] The appendix section provides the income share of all country groups in 1999 and 2020 (based on the categorization of ten countries in each group).

Table 2: Income share of top and bottom ten country groups in 2020

Countries	GDP_pc (2020)	% Share (2020)	Group
Luxembourg	104879.26	48.45%	Top 10 countries
Switzerland	85685.29		
Ireland	78732.55		
Norway	75017.16		
United States	58060.31		
Denmark	56202.17		
Iceland	53188.04		
Sweden	51541.66		
Netherlands	46345.35		
Finland	45009.62		
Ecuador	5315.52	2.44%	Bottom 10 countries
Georgia	4447.66		
Armenia	4021.05		
Indonesia	3757.12		
El Salvador	3632.45		
Moldova	3235.95		
Bolivia	2986.02		
Ukraine	2350.40		
Honduras	2239.01		
Kyrgyz Republic	1102.66		

Tables 3 and 4 divide our GDP per capita data for 1999 and 2020 into deciles and then compare the highest and lowest deciles. We find that the top decile's share was alarmingly 60 times more than the bottom decile in 1999. However, in 2020, the top decile had an income share 38 times higher than the lowest decile, a drop from the 1999 value but still very high. We notice some decrease in inequality, although the lowest decile's share increased only by just 0.19%. The scenario becomes grimmer when we see that the income share of the lowest decile has failed to attain even 1% of the total income of countries in our sample during the period. Furthermore, the wealthiest decile's income share remained essentially consistent throughout the same period. The main difference is that, instead of Iceland in 1999, Ireland entered the top income decile in 2020. Georgia and Armenia, on the other hand, moved up from the lowest income decile in 1999 to the second lowest in 2020. In our dataset, each decile's income share stayed largely unchanged when we compared between 1999 and 2020.[10] The overall picture from tables 3 and 4 is reaffirming the facts that we documented through tables 1 and 2.

Table 3: Income share of countries in highest and lowest deciles in 1999

Countries	**GDP_pc (1999)**	**% Share (1999)**	**Group**
Kyrgyz Republic	689.42	0.59	Lowest decile
Armenia	1210.36		
Moldova	1307.98		
Ukraine	1327.57		
Georgia	1508.66		
Iceland	40725.89	35.57	Highest decile
United States	47360.54		
Denmark	47622.44		
Norway	65768.99		
Switzerland	71583.69		
Luxembourg	87695.34		

Table 4: Income share of countries in highest and lowest deciles in 2020

[10] The appendix section provides the income share of all country groups in 1999 and 2020 (based on the deciles).

Countries	GDP_pc (2020)	% Share (2020)	Group
Kyrgyz Republic	1102.66	0.88	Lowest decile
Honduras	2239.01		
Ukraine	2350.40		
Bolivia	2986.02		
Moldova	3235.95		
Denmark	56202.17	33.93	Highest decile
United States	58060.31		
Norway	75017.16		
Ireland	78732.55		
Switzerland	85685.29		
Luxembourg	104879.26		

Table 5 compares the top ten countries with the highest Gini coefficients (higher inequality) for 1999 and 2020. We notice that the set of countries remain the same in both years for the group except that Costa-Rica replaced El Salvador in 2020. This is consistent with the our previous stylized fact that global inequality has not changed considerably over time. It demonstrates that inequality has a high inertia and is indeed a long-term problem of a country. Table 6 compares variations in the top ten nations with the lowest Gini coefficients (more equality) between 1999 and 2020. Several European countries, like Finland, Norway, Sweden, the Netherlands, and Austria, were unable to maintain their places in the lowest group in terms of Gini coefficients in 2020 as compared to 1999. This hints that inequality has perhaps increased in these advanced countries.

Table 5: Countries with highest Gini coefficient in 1999 and 2020

Countries	Gini coefficient (highest)	Year
Brazil	59	1999
Colombia	58.7	
Ecuador	58.6	
Bolivia	58.1	
Panama	56.5	
Honduras	55.4	
Peru	54.8	
Paraguay	54.6	
El Salvador	52.2	
Chile	52	
Colombia	54.2	2020
Panama	49.6	
Costa Rica	49.3	
Brazil	48.9	
Honduras	48.9	
Ecuador	47.3	
Chile	44.9	
Peru	43.8	
Bolivia	43.6	
Paraguay	43.5	

Table 6: Countries with lowest Gini coefficient in 1999 and 2020

Countries	**Gini coefficient (lowest)**	**Year**
Denmark	23.4	1999
Czech Republic	24.5	
Slovenia	25.4	
Iceland	26	
Finland	27	
Norway	27	
Sweden	27.4	
Slovak Republic	28	
Netherlands	28.1	
Austria	28.4	
Slovak Republic	23.3	2020
Belarus	24.4	
Slovenia	24.6	
Armenia	25.2	
Czech Republic	25.4	
Ukraine	25.6	
Moldova	25.8	
Iceland	26.5	
Belgium	27.1	
Denmark	27.8	

Figure 1 shows that countries with low initial income register higher growth, while countries with high initial income experience growth at a slower rate. This supports the Neoclassical viewpoint that countries with lower initial income are expected to grow at a faster rate.

Figure 1: GDP per capita 1999 and Average GDP per capita growth rate, 1999-2020

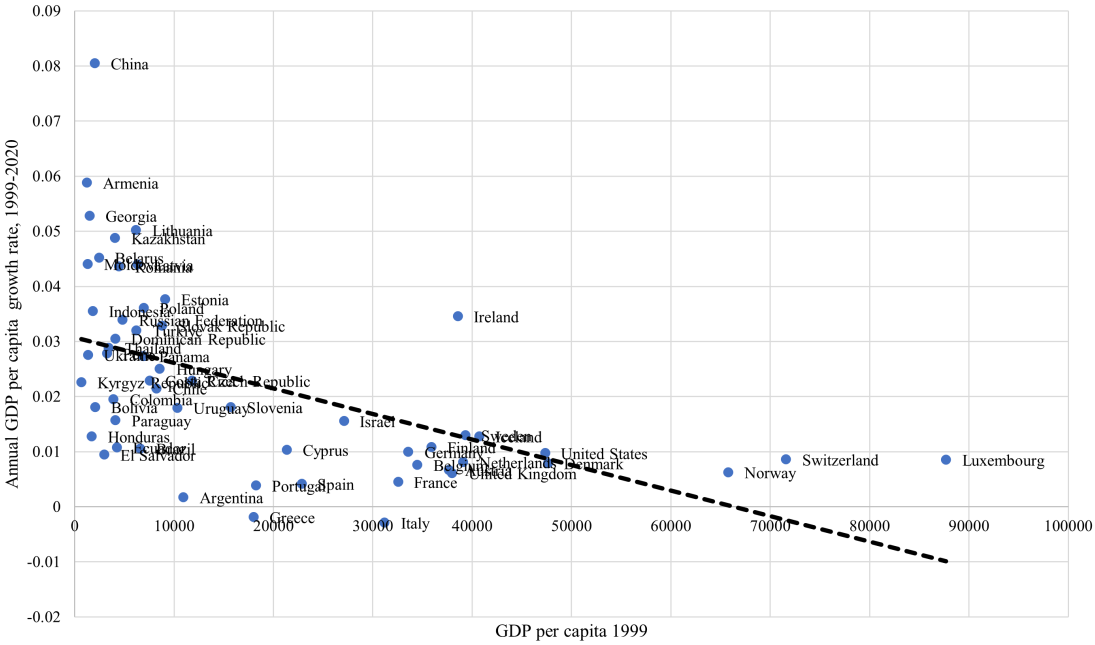
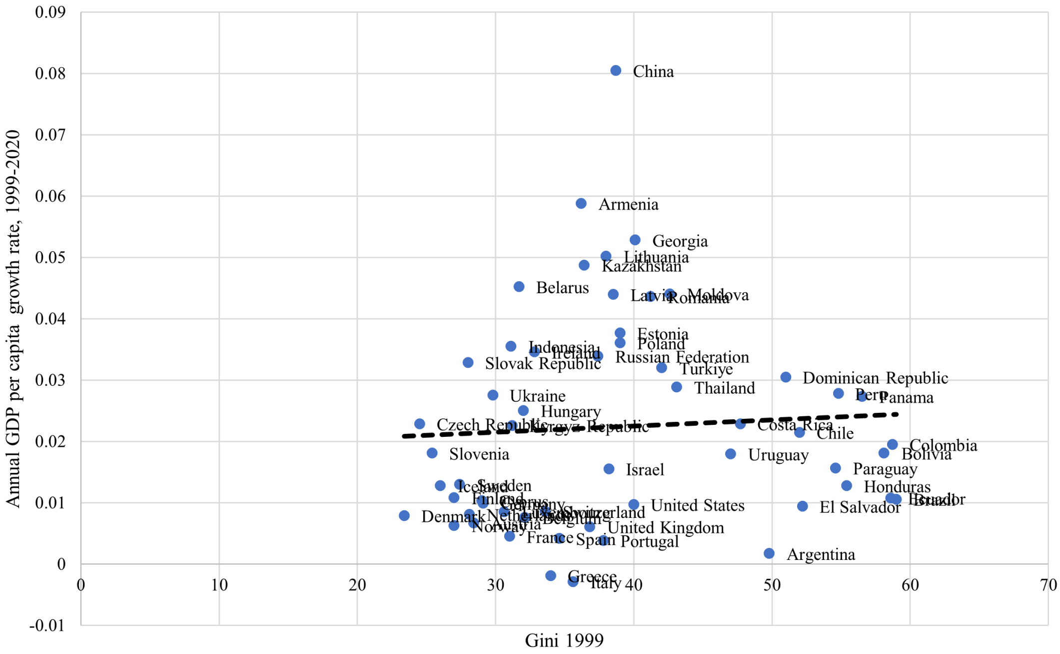


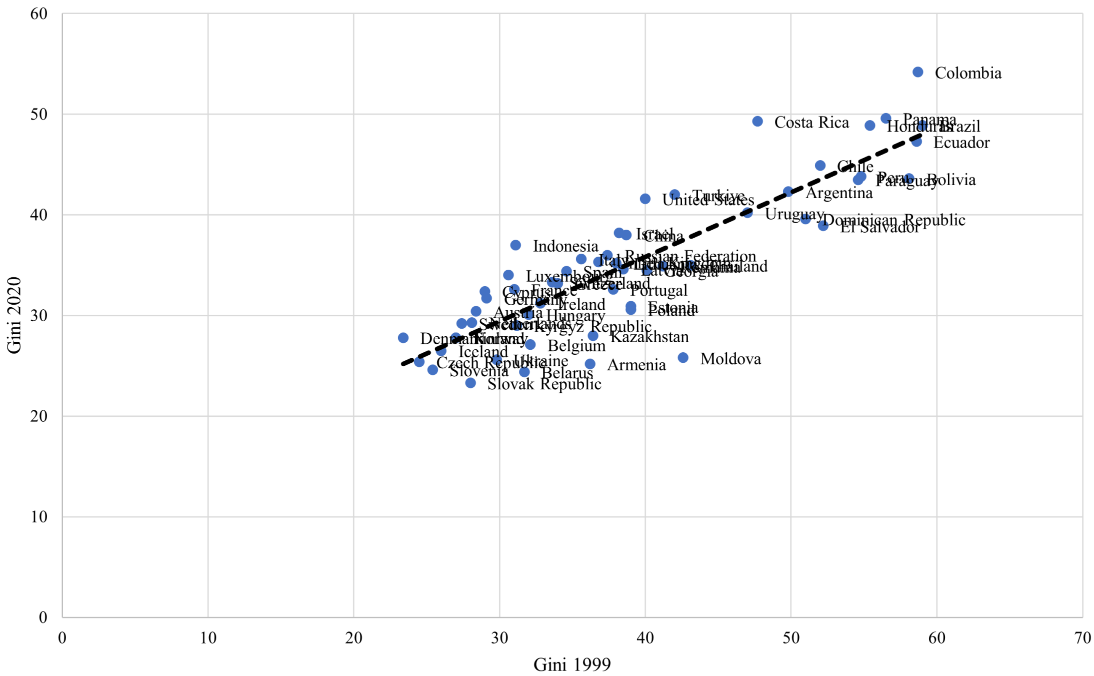
Figure 2 compares the average GDP per capita growth rate during 1999–2000 for the group of countries against the initial Gini coefficient of 1999–2000. It appears that inequality has no association with the average GDP per capita growth rate. Thus, prima facie we do not find any consistent relationship with growth and measure of inequality.

Figure 2: Gini coefficient 1999 and Average GDP per capita growth rate, 1999-2020



Finally, figure 3 checks if there is any significant change in terms of inequality between 1999-00 and 2000-20. One would expect countries that experienced a drop in Gini coefficients to lie below a 45-degree line in a space where the 1999 and 2020 Gini coefficients are plotted on the x- and y-axes, respectively.

Figure 3: Gini coefficient 2020 vs. Gini coefficient 1999



In our case, we notice that the opposite has occurred in the majority of the countries in our data set. A large group of countries are located above the 45-degree line, including advanced economies, indicating an increase in inequality over time. Thus, it becomes more interesting to investigate the impact of inequality on economic growth in the recent past.

3 Estimation Strategy

In econometric analysis, regression coefficients $'\beta'$ reflect inferences or predictions about true population parameters $'\theta'$. The Bayes rule describes how the observed data update the prior beliefs for $'\theta'$ i.e., $p(\theta)$ to posterior beliefs i.e., $p(\theta|data)$. Multiple hypotheses or models M_i can characterize the relationship between ϑ and the data. So, we first compute Posterior Model Probability (PMP), i.e., $p(M_i|data)$, which describes the plausibility of M_i after the data are observed. Thus, PMP selects the best plausible model given the data (model selection). The PMP is fundamental to the BMA framework, as it provides the weights for averaging model coefficients across submodels. It is more appealing to select a specific model that dominates the distribution of PMP and reflects the best approximation of the actual situation. However, there is remaining uncertainty not only about parameters but also about the underlying true model. In this scenario, a Bayesian analysis takes into account both uncertainty regarding the parameters of a specific model and uncertainty across all models. This is accomplished using Bayesian Moving Average (BMA), which uses the combined distribution of a parameter weighted by the PMPs of all candidate models.

From a Bayesian perspective, no model ever totally disappears, and thus, no model completely dominates the relationship, just as no model is ever, without a doubt, the “true” model. Each model represents its own inferences and predictions regarding the outcome variable. However, if one model has a substantially higher probability than the others, it will dominate the average prediction. However, with PMP, there is always uncertainty regarding other smaller models. In this situation, the optimal prediction is obtained by averaging over the models rather than selecting only the arbitrarily largest model.

BMA considers all conceivable scenarios with probability that influence the outcome, and the estimate is obtained through the following equation:

$$p(t) = \sum_i p(t|M_i)p(M_i) \tag{1}$$

The BMA estimate is adjusted as new data becomes available; this information can be referred to collectively as "data," and the BMA estimate becomes:

$$p(t|data) = \sum_i p(t|M_i, data)\, p(M_i|data) \tag{2}$$

The essence of the BMA approach is the ability to swiftly choose models, or more specifically, sets of explanatory variables, that are likely to affect our outcome variable. By averaging across a large set of models, one can determine variables relevant to the data-generating process for a given set of priors used in the analysis. Each model (a set of variables) receives a weight, and the final estimates are constructed as a weighted average of the parameter estimates from each of the models. BMA includes all of the variables within the analysis but reduces the impact of certain variables towards zero through the model weights. These weights are the key feature for estimation via BMA and will depend upon several key features of the averaging exercise, including the choice of prior specified.

The implementation of BMA was first proposed by Leamer (1978) for linear regression models. Consider a linear regression model with a constant term, β_0, and k potential explanatory variables $x_1, x_2, ...x_k$:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \tag{3}$$

Given the number of regressors, we will have 2^k different combinations of right-hand side variables indexed by M_i for $i = 1, 2, 3, ...k^k$. Once the model space has been constructed, the posterior distribution for any coefficient of interest, say β_m, given the data is:

$$p(\beta_m|data) = \sum_i p(\beta_m|M_i, data)p(M_i|data) \tag{4}$$

BMA uses each model's posterior probability, $p(M_i|data)$ as weights. The posterior model probability of M_i is the ratio of its marginal likelihood to the sum of marginal likelihoods over the entire model space and is given by:

$$p(M_i|data) = p(data|M_i)p(M_i)/\sum_i p(data|M_i)p(M_i) \tag{5}$$

where,

$p(data|M_i) = \int p(data|\beta_i, M_i)p(\beta_i|M_i)d\beta$ and β_i is the vector of parameters from modelM_i, $(\beta_i|M_i)$ is a prior probability distribution assigned to the parameters of model M_i, and $P(M_i)$ is the prior probability that M_i is the true model. The estimated posterior means and standard deviations of $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \ . \ . \ . \ , \hat{\beta}_k)$ are then constructed as follows:

$$E[(\hat{\beta})|data) = \sum_i p(M_i|data) \tag{6}$$

$$Var[(\hat{\beta})|data)] = \sum_i (var[\hat{\beta}|data, M_i] + \hat{\beta^2})(M_i|data) - E[\beta|data]^2 \tag{7}$$

BMA is particularly useful when the goal is prediction or parameter estimation in the presence of multiple competing models. BMA is less useful when a single model dominates all others or*does* matter in the process of growth. Specifically, we find when the purpose is quantifying evidence for a set of candidate models. It provides information about estimated coefficients and their standard errors (mean and standard deviation of the posterior distribution), t-ratios, posterior inclusion probabilities (the posterior probability that a variable is included in the model), and one-standard error bands. An regressor is considered robustly correlated with the outcome if the t ratio on its coefficient is greater than one in absolute value or the corresponding one-standard error band does not include zero. Alternatively, the robustness of the regressors can be judged based on their posterior inclusion probabilities. The posterior inclusion probability of 0.5 is roughly equivalent to a t ratio of one in absolute value. (Raftery, 1995 and Masanjala and Papageorgiou, 2008).

BMA can support only a limited number of regressors. Suppose $k_1$is the set of focus regressors and $k_2$are auxiliary regressors. When $k_2$is large, the most binding constraint is expected to be computing time. The time needed for fitting the model with k_2= 30 was 157 hours (6 days and 13 hours) (dataset analyzed by Sala i-Martin, Doppelhofer, and Miller (2004), Ley and Steel (2007), and Magnus, Powell, and Prufer (2010), which includes 67 determinants of the average GDP growth rate per capita for 88 countries from 1960–1996). As a result, depending on the number of explanatory variables, it may be feasible to enumerate and consider 2^k different combinations. In this case, the model space is fully explored. On the other hand, if the number of explanatory variables are large then MCMC sampling is used to explore the model space more efficiently by considering only more likely models given the observed data, for example, the MCMC model composition (MC3) sampling proposed by Madigan and York (1995). In our study, we are working with 15 growth determinants (or control variables), as a result computational time is relatively less, allowing us to enumerate the models.

The BMA methodology requires determining two types of priors: parameter priors (g) on the parameter space and model priors $p(M_i)$ on the model space. These priors are crucial for determining the posterior probabilities (Liang et al., 2008; Feldkircher and Zeugner, 2009; Ciccone and Jarocinski, 2010). In general, priors specify the researcher's information or beliefs before observing the actual data. Since the degree of belief is not particularly strong in the context of growth regressions, uninformative priors are typically employed. For instance, Eicher et al. (2011) and Fernandez et al. (2001) found that the unit information prior (uip) with a uniform model prior tends to provide more accurate predictions than other considered priors. Therefore, for our baseline results, we have used the unit information prior (uip) and a uniform model prior. Moreover, when the number of determinants is small (e.g., fewer than 24), it is generally advisable to use less informative priors (like Unit Information Priors or Uniform priors) to reduce the risk of prior dominance, avoid overfitting, and allow the data to inform the posterior in a more balanced way.

For robustness checks, we examine different combinations of parameter (fixed g) and model priors to explore the effect of income inequality on economic growth. Namely, we use Zellner's g prior structure, which is commonly employed in the literature. Additionally for robustness checks, we applied the following parameter priors: benchmark prior, risk inflation criterion prior (ric), and square root n prior (sqrtn), along with the following model priors: binomial, and beta binomial. We employ the Extreme Bound Analysis method as our last check of robustness. Extreme Bound Analysis (EBA) is utilized as a critical robustness diagnostic to assess the stability of the estimated association between income inequality, quantified by the Gini coefficient, and economic growth. The methodology is primarily based on Leamer's (1983) pioneering work. It systematically changes the control variables in the conditioning set to find the range in which the Gini coefficient stays the same sign, size, and statistical significance. This method lets us find out how strong the relationship between inequality and growth is, or how much it depends on particular model assumptions. EBA makes the outcomes appear more credible and reliable, both in terms of evidence that can be seen and evidence that can be inferred.

4 Results

In this section, we report our primary results from BMA regressions which revolve around the long term economic growth and discusses the impact of inequality on growth. Tables 7 and 8 provide the Posterior Inclusion Probabilities (PIP) as well as the posterior mean and the standard deviation for each regressor. The dependent variables in Tables 7 and 8 are the annual GDP growth rate (agdpgr) and the annual

GDP per capita growth rate (agdppcgr), respectively. The results are obtained after visiting 32,768 models. The posterior model size is 7.33 (i.e. the average number of included regressors). [11]

Table 7: BMA results (dependent variable: annual GDP per capita growth rate)

Variables	Post mean	Post S.D.	PIP	1-S.D. bands
gfcgdp	-0.247	0.033	1	(-0.280, 0.213)
intern	-0.035	0.005	0.999	(-0.043, -0.033)
gi	-0.073	0.025	0.964	(-0.098, 0.047)
pcor	-2.536	0.828	0.962	(-3.365, -1.708)
lexp	-0.164	0.069	0.918	(-0.014, 0.010)
unemp	-0.086	0.036	0.915	(-0.123, -0.049)
hbed	0.153	0.100	0.781	(0.052, 0.253)
trade	0.003	0.003	0.460	(-0.000, 0.006)
log_pop	0.009	0.041	0.079	(-0.032, 0.051)
inf	-0.000	0.003	0.058	(-0.004, 0.002)
geegdp	-0.000	0.000	0.055	(-0.000, 0.000)
oilrent	0.001	0.009	0.038	(-0.008, 0.010)
mphone	-0.000	0.031	0.036	(-0.001, 0.000)
ngrent	-0.000	0.031	0.030	(-0.032, 0.030)
mrent	0.001	0.012	0.030	(-0.011, 0.013)
constant	23.924	6.060	1	(7.423, 11.360)

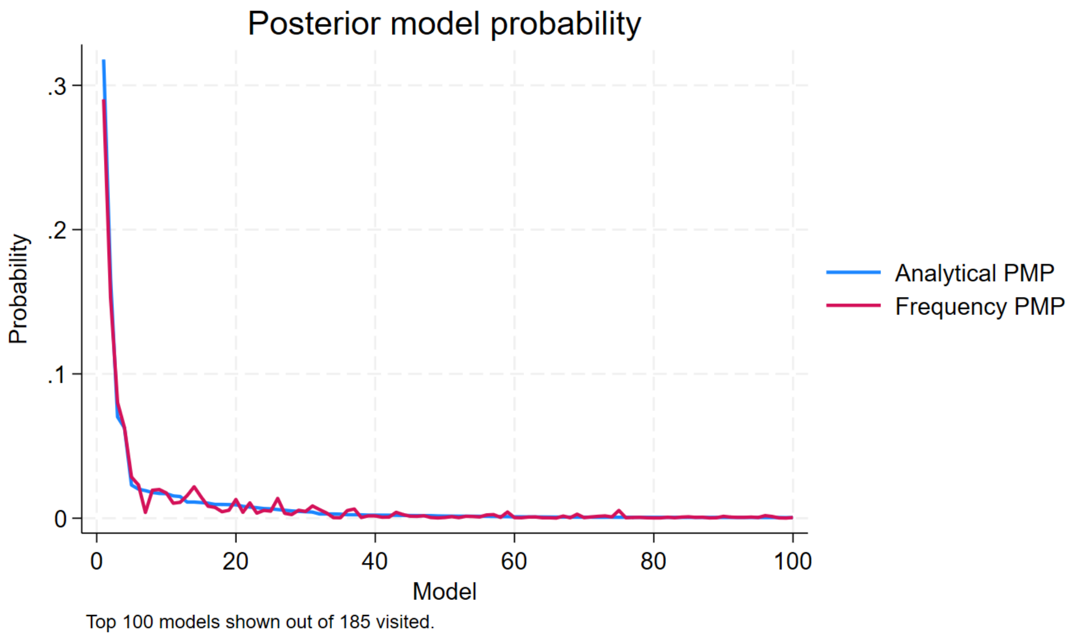
Note: The number of observations and models are 1,232 and 32,768, respectively.

[11] We conducted robustness checks by comparing the results of Bayesian Model Averaging (BMA) regressions with simple Ordinary Least Squares (OLS) regressions. Sensitivity analyses are also performed by changing one of our explanatory variables, namely, government expenditure on education as a percentage of GDP (geegdp), with government expenditure on education as a percentage of total expenditure (geetge), as shown in Appendix A.3. Our primary results remain unchanged. Results are available on request.

The results suggest that inequality indicator (Gini coefficient) with high posterior inclusion probability of 0.96 exerts a negative impact on economic growth. Among other variables share of governments final consumption tops the list with PIP value of 1. However, it has an adverse effects on growth as it ends up with negative sign. Number of hospital beds which is a proxy for health infrastructure plays a positive and significant role with high posterior inclusion probability. Internet measure has positive effect with 0.99 PIP. Trade indicator although with rather moderate posterior inclusion probability of the moderate PIP of 0.46 contributes for enhancement of growth. Unemployment has a PIP of 0.91 with negative sign. Thus, higher unemployment is naturally associated with lower lower economic growth. Political corruption has a PIP of 0.96 with negative sign. Its magnitude in absolute terms is also large (2.53). This indicates that corruption reduces economic growth, as it distorts resource allocation, weakens institutional efficiency, and undermines investor confidence. Lastly, life expectancy has a PIP of 0.91 with a negative coefficient, indicating an inverse association with economic growth, which might be due to the end of the demographic transition in the sample countries. Now, reasons for inequality playing a detrimental role on growth is commonly due to the believe that income inequality fuels social dissatisfaction and raises the threat of social, political, and economic unrest in the country. This negative relationship has been confirmed by numerous empirical findings.[12] Our results did not find any other variable with relatively high posterior inclusion probability. These results are consistent with Evans and Timberlake (1980) and Lundberg and Squire (2003). The last column lists down the credible intervals for the variables. We have relatively narrow credible intervals suggesting high confidence in parameter estimates across models.

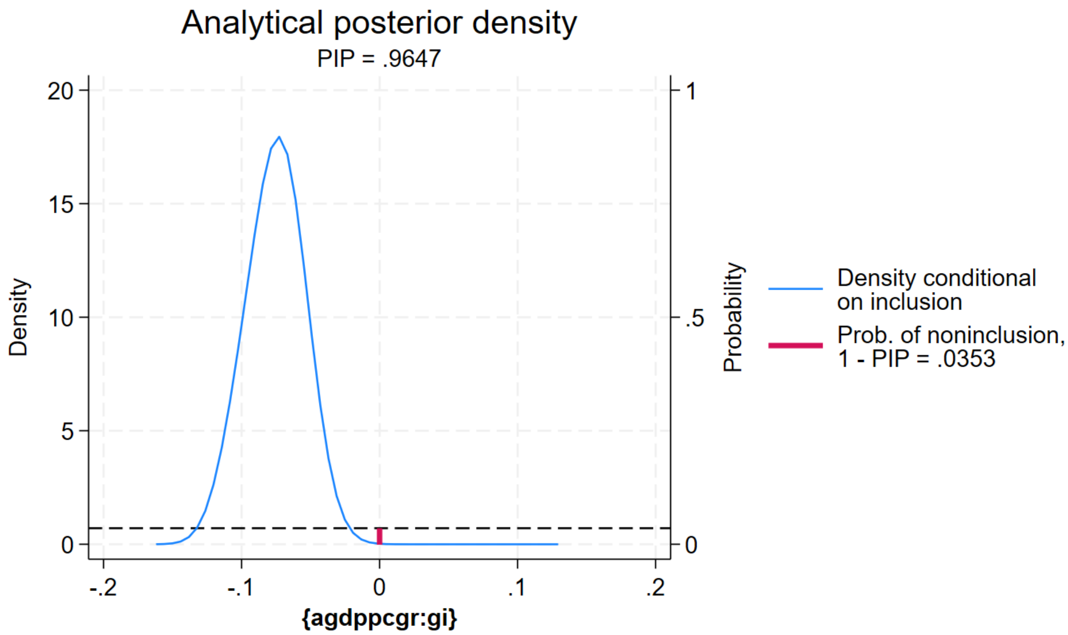
Figure 4: Posterior model probability (dependent variable: annual GDP per capita growth rate)

[12]See Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996) and Panniza (2002).



In Bayesian Model Averaging (BMA) we can generate model-probability plots after performing BMA regression. These plots provide a graphical summary of the models visited during the BMA process, displaying their Posterior Model Probabilities (PMPs). This visualization is particularly useful for assessing the convergence of the Markov chain Monte Carlo (MCMC) algorithm used in BMA and for identifying models with the highest PMPs. The analytical and MCMC frequency-based or simply frequency posterior probability distributions should be close when the model space is sufficiently explored. The figure 4 confirms that Analytical PMP and frequency PMP has coincided. The two lines are nearly identical, which is a strong indication of convergence.

Figure 5: Posterior density of Gini coefficient (dependent variable: annual GDP per capita growth rate)



In the Bayesian Moving Average (BMA) method, the posterior density graph represents the probability distribution of parameters (e.g., mean or coefficients) after updating beliefs with observed data. This is typically done using Markov Chain Monte Carlo (MCMC) or other Bayesian inference techniques. We used MCMC to generate the figure 5. The x-axis represents possible values of the BMA coefficient (θ). The y-axis represents the probability density. The peak shows the most probable value of θ given the data. In our case the peak is around -0.07 for Gini coefficient. In BMA, we left the model selection to the estimation procedure itself. It considered all possible permutations and combinations to conclude that inequality is a substantial and significant determinant of growth and that there exists an inverse relationship between inequality and growth.

[13]

Table 8: BMA results (dependent variable: annual GDP growth rate)

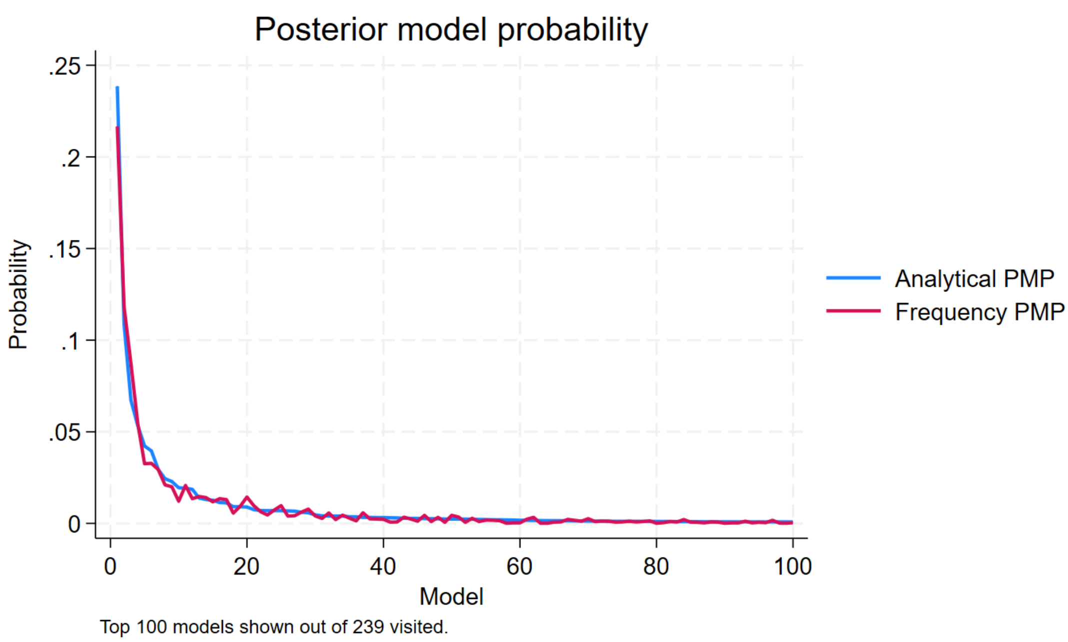
[13] We have done the similar exercise with the five year panel data and results are on similar lines. Results are available on request.

Variables	Post mean	Post S.D.	PIP	1-S.D. bands
gfcgdp	-0.223	0.034	1	(-0.258, -0.188)
intern	-0.044	0.006	1	(-0.050, -0.038)
unemp	-0.143	0.026	0.999	(-0.170, -0.116)
trade	0.010	0.002	0.990	(0.007, 0.012)
pcor	-1.288	0.782	0.814	(-2.070, -0.505)
gi	-0.037	0.026	0.729	(-0.063, -0.010)
oilrent	0.053	0.057	0.530	(-0.003, 0.110)
hbed	0.028	0.059	0.225	(-0.031, 0.088)
lexp	-0.008	0.030	0.113	(-0.039, 0.021)
mrent	0.008	0.033	0.082	(-0.025, 0.041)
log_pop	0.007	0.034	0.073	(-0.027, 0.042)
mphone	-0.000	0.001	0.069	(-0.001, 0.001)
ngrent	0.003	0.043	0.039	(-0.039, 0.047)
geegdp	-0.000	0.000	0.036	(-0.000, 0.000)
inf	-0.000	0.001	0.030	(-0.001, 0.001)
constant	11.312	2.940	1	(7.993, 11.546)

Note: The number of observations and models are 1,232 and 32,768, respectively.

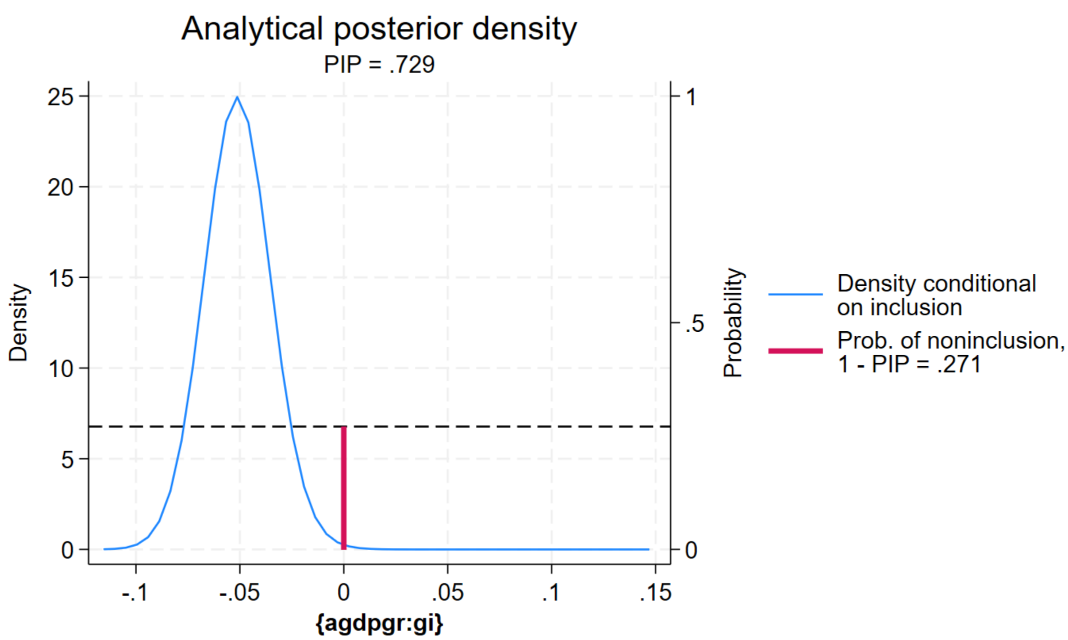
In Table 8, we conduct the same exercise, but we replace our dependent variable, per capita GDP growth, by the GDP growth rate. Our measure of inequality has a negative sign and a posterior inclusion probability (PIP) of 0.72. Like before, the negative sign of inequality reconfirms an inverse relationship with GDP growth. The coefficient of inequality has an absolute value is 0.03. The magnitude of the coefficient decreases from 0.07 (refer to Table 7) to 0.03, but the core of our findings remains unchanged. In all circumstances, a PIP value greater than 0.5 indicates that inequality is a major and significant variable that must be included while explaining growth. The negative sign and magnitude of the coefficient indicate that a one-basis-point increase in inequality could limit GDP growth by roughly three to four basis points. Among other variables, digital infrastructure captured by the internet connection has a PIP value of 1 with mean coefficient of -0.04. Needless to mention, digital infrastructure has become an integral part of economic growth. Notably, it turns out that the government's share of final consumption remains negative, with a PIP value of 1 in Table 8. It echoes the similar result we obtained for the government's share of final consumption in Table 7. The magnitude of the coefficient marginally drops, but the negative value of the coefficient with a PIP value of one signifies a negative impact of the government's share of final consumption on growth. Finally the political corruption and unemployment rate reflects expected negative sign in both tables. In both tables and in all cases the PIP value is above 0.90. This reaffirms that the political corruption and unemployment rate is one of the most important and significant variables in explaining growth of an economy. The variables' credible intervals are listed in the final column. High confidence in parameter estimations across models is indicated by our narrow credible intervals.

Figure 6: Posterior model probability (dependent variable: annual GDP growth rate)



Analytical PMP generally shows higher inequality (Gini > 0.5) due to extreme event variations. Frequency PMP tends to have a lower Gini (< 0.3) due to statistical smoothing of data. Gini Coefficient Analysis in PMP helps decision-makers choose the right method based on whether they prioritize extreme event modeling (higher Gini) or consistency (lower Gini). However in our analysis like previous here also we note that both analytical and frequency PMP has coincided which is a strong signal of convergence. In both occasions convergence of analytical and freqency PMP have been achieved. Convergence means that both analytical and frequency methods produce consistent PMP values, reducing uncertainty in decision-making. When Analytical PMP and Frequency PMP yield similar estimates, their convergence indicates a robust and reliable estimation.

Figure 7: Posterior density of Gini coefficient (dependent variable: annual GDP growth rate)



In Bayesian statistics, the posterior density graph is a visual representation of the probability distribution of a parameter after incorporating observed data. The analytical posterior density graph refers to a mathematically derived (rather than purely sampled) posterior distribution, often obtained through conjugate priors or exact probability density functions (PDFs). The posterior density plot shows how probable different values of θ are after updating beliefs with observed data. We note that that the spread is narrow which indicates that data strongly determines θ. The peak occurs around negative 0.04. Thus as per our data and estimation the most probable value for the Gini coefficient is -0.04. It is consistent with our previous results.

Table 9a: Gini coefficient estimates for different parameter and model priors used (dependent variable: annual GDP per capita growth rate)

Parameter/Model priors	Uniform	Binomial	Beta binomial
Unit information prior (uip)	0.964 (-0.073)	0.964 (-0.073)	0.961 (-0.073)
Benchmark prior	0.964 (-0.073)	0.964 (-0.073)	0.961 (-0.073)
Risk inflation criterion prior (ric)	0.974 (-0.069)	0.974 (-0.069)	0.977 (-0.068)
Square root n prior (sqrtn)	0.981 (-0.064)	0.981 (-0.064)	0.989 (-0.061)

Note: The number of observations and models are 1,232 and 32,768, respectively. PIP values are reported with coefficient in parenthesis.

Table 9b: Gini coefficient estimates for different parameter and model priors used (dependent variable: annual GDP growth rate)

Parameter/Model priors	Uniform	Binomial	Beta binomial
Unit information prior (uip)	0.729 (-0.037)	0.729 (-0.037)	0.709 (-0.036)
Benchmark prior	0.729 (-0.037)	0.729 (-0.037)	0.709 (-0.036)
Risk inflation criterion prior (ric)	0.792 (-0.038)	0.792 (-0.038)	0.793 (-0.038)
Square root n prior (sqrtn)	0.842 (-0.038)	0.842 (-0.038)	0.876 (-0.038)

Note: The number of observations and models are 1,232 and 32,768, respectively. PIP values are reported with coefficient in parenthesis.

A popular method in the literature is the Zellner's g prior structure, which is what we employ. According to Feldkircher and Zeugner (2009), parameter g indicates the relative importance of the prior variance vs the variation shown in the data. Choosing a small g causes the prior coefficients to have little variance, which lowers the coefficients to zero. On the other hand, a large g indicates researchers' uncertainty about zero coefficients and gives the data more importance. It makes the assumption that the error variance and constant priors are spread equally. The most common scenario in BMA literature, according to Mora-Benito (2012), is the binomial distribution, in which each covariate is incorporated in the model with a probability success θ. We use the same model prior. However, in Table 9a (dependent variable: annual GDP per capita growth rate) and Table 9b (dependent variable: annual GDP growth rate), we present PIP and Gini coefficients for various combinations of parameter priors and model priors for both dependent variables in order to verify the robustness of our findings. The coefficient estimate is bolded and enclosed in parenthesis, while the PIP is the number without parenthesis. Unit information prior (uip), benchmark prior, risk inflation criterion prior (ric), and square root n prior (sqrtn) are the parameter priors that we employed. Uniform, Binomial, and Beta binomial are model priors that combine with parameter priors. We distinctly notice that PIP values are not decreasing significantly in any combinations and the coefficient estimates are almost same across the both tables (refer to table 7 and 8 for comparison). The fact that our results are independent of any specific model and parameter prior choice is confirmed by this robustness exercise. Our results remain unchanged after the robustness checks.[14]

[14]The results of the robustness tests based on the extreme bounds analysis (EBA) are presented in appendix Tables A.5 and A.6, where the Gini coefficient serves as the main explanatory variable. Table A.5, which uses the annual GDP per capita growth rate as the dependent variable, shows that the estimated coefficients for the Gini coefficient range narrowly between –0.123 and –0.119 across 1,001 model combinations with four control variables. The consistently negative coefficients suggest that higher income inequality is associated with slower per capita economic growth. In contrast, Table A.6, which employs the annual GDP growth rate as the dependent variable, reports that the estimated coefficients for the Gini coefficient vary between –0.076 and 0.104. Although the signs of the coefficients vary slightly, extreme changes in the set of control variables do not substantially alter the inequality–growth relationship. Overall, the results confirm the robustness

Based on these findings, we conclude that the fundamental finding of our study is that income disparity has a negative and considerable impact on a country's economic growth. Our conclusion is reached after incorporating factors that may influence this relationship in the regression models. Our findings are in alignment with Panizza (2002), Peng (2008), and Persson and Tabellini (1994). The following section concludes.

5 Conclusion

The primary purpose of this research is to reassess the nature and relevance of the relationship between inequality and growth. Since Kuznet's (1954) inverted U-shaped relationship between inequality and growth came into existence, there has been interest in the dynamics of inequality and growth. The Kuznet curve worked well until 1980 for developed and developing economies, but after 1980, the overall picture changed. The existing literature does not clearly agree on whether inequality has a negative or positive influence on growth. Does it even matter? As a result, we still don't know exactly how inequality affects growth or how these critical macroeconomic variables relate to one another. This allowed us to undertake a more in-depth investigation using an econometric method appropriate for the task.

We use an advanced estimation technique to reduce measurement error and control for time-invariant omitted variables through a panel data set. Specifically, we use the Bayesian Moving Average (BMA) method to decipher the much-debated nexus between inequality and economic growth for a set of 56 countries for the time period 1999–2020. We acknowledge that although the data on inequality have improved significantly, measurement error may still be an issue. Our Bayesian estimation results reveal that inequality has a significant and negative impact on growth. We found that if the Gini coefficient increases by 10 basis points, an economy's per capita growth rate has the potential to fall by 5 basis points. Our primary finding

of the findings, income inequality negatively affects economic growth.

is consistent with prior research, which indicated a negative association between inequality and growth. In all cases, the posterior inclusion probability of inequality is close to 1. Our results remain robust to sensitivity analysis using different dependent variables, different parameter priors and model priors.

Appendix

Table A.1 Income share of deciles in 1999 and 2020

Deciles	GDP_pc (% share, 1999)	GDP_pc (% share, 2020)
1	0.60	0.88
2	1.29	1.99
3	1.84	2.35
4	2.95	4.55
5	4.20	5.79
6	4.70	6.10
7	10.65	9.83
8	15.67	13.65
9	22.53	20.92
10	35.57	33.94

Table A.2 Income share of country groups in 1999 and 2020

Country groups	GDP_pc (% share, 1999)	GDP_pc (% share, 2020)
1	50.85	48.45
2	29.08	25.55
3	10.75	12.59
4	5.59	8.19
5	2.96	4.07
6	0.77	1.15

Table A.3 List of variables

Variables	**Abbreviations**
GDP growth (annual %)	agdpgr
GDP per capita (constant 2015 US$)	agdppc
GDP per capita growth (annual %)	agdppcgr
General government final consumption expenditure (% of GDP)	gfcgdp
Government expenditure on education, total (% of GDP)	geegdp
Government expenditure on education, total (% of government expenditure)	geetge
Gross fixed capital formation (% of GDP)	gfcf
Hospital beds (per 1,000 people)	hbed
Individuals using the Internet (% of population)	intern
Inflation, GDP deflator (annual %)	inf
Life expectancy at birth, total (years)	lexp
Mineral rents (% of GDP)	mrent
Mobile cellular subscriptions (per 100 people)	mphone
Natural gas rents (% of GDP)	ngrent
Oil rents (% of GDP)	oilrent
Population growth (annual %)	popgr
Total population	totpop
Trade (% of GDP)	trade
Unemployment, total (% of total labor force) (modeled ILO estimate)	unemp
Political corruption index	pcor

Table A.4 List of countries

Argentina	Israel
Armenia	Italy
Austria	Kazakhstan
Belarus	Kyrgyz Republic
Belgium	Latvia
Bolivia	Lithuania
Brazil	Luxembourg
Chile	Moldova
China	Netherland
Colombia	Norway
Costa Rica	Panama
Cyprus	Paraguay
Czech	Peru
Denmark	Poland
Dominician Republic	Portugal
Ecuador	Romania
El Salvador	Russian Federation
Estonia	Slovak Republic
Finland	Slovenia
France	Spain
Georgia	Sweden
Germany	Switzerland
Greece	Thailand
Honduras	Turkiye
Hungary	Ukraine
Iceland	United Kingdom
Indonesia	United States
Ireland	Uruguay

Table A.5: Robustness test using extreme bounds analysis (dependent variable: annual GDP per capita growth rate)

Bounds	Coefficient	t-stat	p-value	95% CI
Minimum	-0.123	-8.261	0.076	(-0.312, 0.066)
Maximum	-0.119	-7.960	0.079	(-0.030, 0.071)

Note: The analysis considers a total of 1,001 model combinations with 4 regressors. The reported bounds are based on a 92% confidence interval (CI) specification.

Table A.6: Robustness test using extreme bounds analysis (dependent variable: annual GDP growth rate)

Bounds	Coefficient	t-stat	p-value	95% CI
Minimum	-0.076	-5.155	0.122	(-0.256, 0.112)
Maximum	0.104	6.209	0.101	(-0.108, 0.316)

Note: The analysis considers a total of 1,001 model combinations with 4 regressors. The reported bounds are based on a 87% confidence interval (CI) specification.

References

[1] Acemoglu, D., Johnson, S., & Robinson, J. A. (2002). Reversal of fortune: Geography and institutions in the making of the modern world income distribution. The Quarterly journal of economics, 117(4), 1231-1294.

[2] Aghion, P., Caroli, E., & Garcia-Penalosa, C. (1999). Inequality and economic growth: the perspective of the new growth theories. Journal of Economic literature, 37(4), 1615-1660.

[3] Ahluwalia, M. S. (1976). Inequality, poverty and development. Journal of development economics, 3(4), 307-342.

[4] Alesina, A., & Rodrik, D. (1994). Distributive politics and economic growth. The quarterly journal of economics, 109(2), 465-490.

[5] Bhorat, H., & van der Westhuizen, C. (2008, May). Economic growth, poverty and inequality in South Africa: the first decade of democracy. In Development Policy Research Unit Conference (Vol. 5, pp. 27-29).

[6] Bigsten, A. (1983). Income distribution and development; theory, evidence, and policy.

[7] Chen, S., & Ravallion, M. (2010). The developing world is poorer than we thought, but no less successful in the fight against poverty. The Quarterly Journal of Economics, 125(4), 1577-1625.

[8] Cline, W. R. (1975). Distribution and development: A survey of literature. Journal of Development Economics, 1(4), 359-400.

[9] Corneo, G., & Jeanne, O. (2001). On relative-wealth effects and long-run growth. Research in Economics, 55(4), 349-358.

[10] Corneo, G., & Jeanne, O. (2001). Status, the distribution of wealth, and growth. Scandinavian Journal of Economics, 103(2), 283-293.

[11] Edwards, S. (1997). Trade policy, growth, and income distribution. The American Economic Review, 87(2), 205-210.

[12] Evans, P. B., & Timberlake, M. (1980). Dependence, inequality, and the growth of the tertiary: A comparative analysis of less developed countries. American Sociological Review, 531-552.

[13] Fishman, A., & Simhon, A. (2002). The division of labor, inequality and growth. Journal of Economic Growth, 7, 117-136.

[14] Forbes, K. J. (2000). A reassessment of the relationship between inequality and growth. American economic review, 90(4), 869-887.

[15] Galor, O., & Tsiddon, D. (1997). Technological progress, mobility, and economic growth. The American Economic Review, 363-382.

[16] Gottschalk, P. (1997). Inequality, income growth, and mobility: The basic facts. Journal of Economic Perspectives, 11(2), 21-40.

[17] Halter, D., Oechslin, M., & Zweimüller, J. (2014). Inequality and growth: the neglected time dimension. Journal of economic growth, 19, 81-104.

[18] Helpman, E. (1997). R&D and productivity: the international connection.

[19] Kaldor, N. (1957). A model of economic growth. The economic journal, 67(268), 591-624.

[20] Knight, K. (1976). Matrix organization: A review. Journal of Management Studies (Wiley-Blackwell), 13(2).

[21] Krueger, D., & Perri, F. (2001). Does income inequality lead to consumption inequality? empirical findings and a theoretical explanation. NYU, Unpublished Working paper.

[22] Krueger, D., & Perri, F. (2003). On the welfare consequences of the increase in inequality in the United States. NBER macroeconomics annual, 18, 83-121.

[23] Krueger, D., & Perri, F. (2006). Does income inequality lead to consumption inequality? Evidence and theory. The Review of Economic Studies, 73(1), 163-193.

[24] Lewis, W. A. (1954). Economic development with unlimited supplies of labour.

[25] Ley, E., & Steel, M. F. (2007). Jointness in Bayesian variable selection with applications to growth regression. Journal of Macroeconomics, 29(3), 476-493.

[26] Li, H., & Zou, H. F. (1998). Income inequality is not harmful for growth: theory and evidence. Review of development economics, 2(3), 318-334.

[27] Lundberg, M., & Squire, L. (2003). The simultaneous evolution of growth and inequality. The economic journal, 113(487), 326-344.

[28] Magnus, J. R., Powell, O., & Prüfer, P. (2010). A comparison of two model averaging techniques with an application to growth empirics. Journal of econometrics, 154(2), 139-153.

[29] Masanjala, W. H., & Papageorgiou, C. (2008). Rough and lonely road to prosperity: a reexamination of the sources of growth in Africa using Bayesian model averaging. Journal of applied Econometrics, 23(5), 671-682.

[30] Panizza, U. (2002). Income inequality and economic growth: Evidence from American data. Journal of Economic Growth, 7, 25-41.

[31] Partridge, M. D. (1997). Is inequality harmful for growth? Comment. The American Economic Review, 87(5), 1019-1032.

[32] Peng, B. (2008). Relative deprivation, wealth inequality and economic growth. Journal of Economics, 94(3), 223-229.

[33] Perotti, R. (1996). Growth, income distribution, and democracy: What the data say. Journal of Economic growth, 1, 149-187.

[34] Persson, T., & Tabellini, G. (1991). Is inequality harmful for growth? Theory and evidence.

[35] Pritchett, L. (1997). Divergence, big time. Journal of Economic perspectives, 11(3), 3-17.

[36] Raftery, A. E. (1995). Bayesian model selection in social research. Sociological methodology, 111-163.

[37] Rangel, L. A., Andrade, J., & Divino, J. A. (2008). Economic growth and income inequality in Brazil: Analyzing the comparable minimum areas. Retrieved March, 21, 2009.

[38] Rehme, G. (2007). Education, economic growth and measured income inequality. Economica, 74(295), 493-514.

[39] Rodrik, D. (2005). Growth strategies. Handbook of economic growth, 1, 967-1014.

[40] Saith, A. (1983). Development and distribution: A critique of the cross-country U-hypothesis. Journal of development economics, 13(3), 367-382.

[41] Sala-i-Martin, X., Doppelhofer, G., & Miller, R. I. (2004). Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. American economic review, 94(4), 813-835.

[42] Voitchovsky, S. (2005). Does the profile of income inequality matter for economic growth? Distinguishing between the effects of inequality in different parts of the income distribution. Journal of Economic growth, 10, 273-296.

[43] Yitzhaki, S. (1979). Relative deprivation and the Gini coefficient. The quarterly journal of economics, 93(2), 321-324.

[44] Zagha, R. (2013). India's inequality: An uneasy reconciliation with economic growth.