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The Interactions of Public Debt, Income Inequality and Economic Growth for U.S. States: A Bayesian Non-Parametric Analysis

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Abstract: A set of Bayesian priors using appropriate models is used to examine the relationship between public debt, income inequality, and economic growth for U.S. states over the period 1987-2011. Our results suggest that both public debt and income inequality has negative effect on per-capita GDP growth during this time period. At the same time, our results also suggest that there is a role of government policy in affecting economic growth, through appropriate investments in public capital, human capital, and technological innovations to improve economic growth. Model validation is performed using Beta process priors of linear regression model and this validation confirms the main findings of the study.

Keywords: Public Debt, Income inequality, Bayesian Non-parametric Analysis

1. Introduction

The combination of public debt and income inequality is producing a negative dynamic on economic growth for U.S. states, and this negative dynamic is translating into a vicious cycle of downward spiral further on poverty and income inequality. Several reasons can be cited for the rise in public debt for U.S. states. First, the rapid growth in health care costs faced by state governments is exceeding the growth in revenue growth in recent decades. Consequently, Medicaid has replaced elementary and secondary education as the largest state spending since 2009 (Zhao and Coyne, 2013). Second, both state and local governments face large unfunded pension and other post-employment benefits (OPEB) liabilities. A recent study by the State Budget Crisis Task Force (2012) points out that unfunded retirement benefits liabilities create large demands on state revenue, thus potentially affecting state and local budgets negatively.

The consequences of growth in public debt for states have both short-run and long-run implications. First, increase in fiscal burden could increase intergenerational inequity by

shifting the burden to future generations in the long-run. Second, state and local governments may have to cut down on public services, such as education, health, and transportation services, which may adversely affect the lower income groups more severely in the short-run. Finally, when the credit ratings of state and local governments suffer, interest rates increase which drive up borrowing costs of states. Under certain conditions, a severe lack of fiscal sustainability might lead to investors fleeing the bond markets, which can create financial distress (Cooper and Walsh, 2010).

Along with the growth in public debt of states, income inequality is on the rise in the United States (Stiglitz, 2015). According to Stiglitz, first, when equality of opportunity declines, many households will be working at below the minimum wage rate at low paying jobs. This will lead to decline in total consumption as the marginal propensity to consume for poor individuals is always higher than those in the higher income brackets. Second, many of the distortions that affect the preferential tax treatment for special interest groups, such as the financial and banking industry will lead to economy-wide inefficiency. This will lead to individuals self-selecting disciplines such as finance than in more productive sectors of the economy, such as in science, technology and engineering. Third, the federal government has cut down investments in infrastructure, R&D, and education & health. These cutbacks will have significant negative impact on productivity growth and thus affect economic growth negatively through its effect on production and income. Fourth, the financial industry largely functions as a market in speculation activities rather than a tool for promoting economic growth. The financial sector gets rents out of it markets in debit and credit card fees, and also on fees charged to merchants, which gets passed on to consumers. In recent years, the financial sector has accounted for some 40 percent of all corporate profits, and thus private returns and social returns deviate from each other significantly. Finally, with the growth in income inequality, student debt has become an integral part of American income inequality. During the great recession, tuition costs at public universities increased by 27 percent during the past five years. With tuition costs soaring, incomes declining, and little support from the federal government, total student debt is now around $1 trillion. Total student debt has surpassed total credit card debt.

The implication of the rise in public debt and income inequality in the U.S. is that youth unemployment is around 20 percent in the U.S., with one out of six Americans looking for a full-time job but not able to find one; one out of seven Americans are on food stamps and is suffering from food insecurity. In some states, spending on prisons has at times exceeded that on universities with the consequence that there has been a significant depreciation of human capital, making the economy less productive over time. During last year, the top 1 percent of income earners took home 22 percent of the nation's income; while the top 0.1 percent took 11 percent. Ninety five percent of all income gains since

2009 have gone to the top 1 percent since 2009. American inequality started increasing since the mid 1980s, when a tax decrease was given to the rich, and there was deregulation on financial sector transactions. The financial sector took advantage of this situation as commercial banks diversified into investment banking to get higher returns on its products and services. At the same time, the federal government continued under-investing in infrastructure, R&D investments and education, which reinforced the inequalities in income and opportunities.

In light of the above, we make the following contributions to the existing literature. First, we consider a Bayesian model averaging (BMA) framework to understand the interactions between public debt, income inequality and economic growth (Durlauf et al., 2005). As model uncertainty is ubiquitous in the economic growth literature, we believe that linear regression models do not adequately capture the quantiles of the distribution. The implementation of BMA involves solving the challenges in Bayesian statistics. For BMA, the prior has two parts: a prior for the parameters of the each model, and the prior probability of each model. If substantial prior information is available and can be readily used as a probability distribution, this should be used. However, if the prior information is small relative to the information in the data, then it makes sense to use default priors. In the case of interactions of public debt and income inequality and its effect on economic growth, prior information is small relative to the information on the data. Thus, we consider 4 candidate default prior parameters and 5 measures of income inequality. This gives us 20 set of estimates of the effect of public debt and its interactions with income inequality on economic growth. We evaluate the predictive mean using the mean squared error, and the entire predictive distribution using two different scoring methods. Second, we consider five different income inequality measures (both population wide measures and household based measures). These measures are Gini coefficient, Atkinson measure, top 1 percent income share, top 10 percent income share, and Theil measure of income inequality.

The rest of the paper is organized as follows. Section 2 provides an overview of the literature on public debt, income inequality and economic growth with a particular emphasis on U.S. states. Section 3 gives a discussion of Bayesian model averaging and the empirical modeling framework on Bayesian priors and model choice. Section 4 discusses results. Finally Section 5 concludes.

2. An Overview of the Empirical Literature

2.1. Relationship between Public Debt and Economic Growth

Reinhart and Rogoff (2010a and 2010b) find that high levels of debt are negatively correlated with economic growth, but there is no link between debt and growth when

public debt is below 90 percent of GDP. They demonstrate that in the high debt group, median growth is approximately 1 percentage point lower and average growth is nearly 4 percentage points lower than in other groups. Using this approach, Minea and Parent (2012) find that public debt is negatively correlated with growth when the debt to GDP ratio is above 90 percent and below 115 percent. However, they also find that the correlation between debt and growth becomes positive when debt exceeds 115 percent of GDP. They suggest that the results of Reinhart and Rogoff should be taken as caution due to the complex non-linearities and outliers in the data which may affect the exogenous thresholds.

In the same light, Afonso and Jalles (2013) consider a sample of OECD countries during the period 1970-2008. They find that the average growth rates over the period of countries with low debt (debt to GDP ratio < 30%) is similar to that of high debt (debt to GDP ratio >90%) are similar. Thus, they suggest that Reinhart and Rogoff results should be interpreted with caution both in terms of outliers in the data and the complex non-linearities in the relationship between public debt and economic growth.

Zhao and Coyne (2013) develop and estimate a new measure of state and local fiscal sustainability called the "trend gap". The study finds that the nationwide per capita trend gap has grown over the past three decades. As a result, by the late 2000s the state and local government sector faced a large shortfall in fiscal sustainability. Both the social insurance and income programs have played a major role in the growth of the trend gap. In addition, the study finds that there are large and growing disparities across states in fiscal sustainability as measured by the trend gap. One of the major reasons behind this trend is cuts in federal grants that are causing considerable fiscal stress to state and local governments. As there are serious downside risks that are outside the control of state and local governments, the study concludes that it is unlikely that trend gaps will decline significantly in the short-run.

The issue of endogeneity is present in the relationship between public debt and economic growth relationship. The link between public debt and economic growth could be driven by the fact that it is low economic growth that leads to high levels of public debt (Reinhart etal., 2012). In addition, it is plausible that the observed correlation between debt and growth could be due to a third factor that affects both these variables. Using lagged debt measures mitigates the endogeneity problem but does not resolve it. Assessing the presence of a causal relationship between debt and growth requires finding an instrumental variable that has a direct effect on debt but no direct effect on economic growth (Panizza and Presbetire, 2013).

Kumar and Woo (2010) study the relationship between debt and growth in a sample of 30 advanced and emerging market countries over the period 1970-2007. They estimate their

model with different methods and argue that the system GMM estimation allows them to address the endogeneity issue. Their results imply that a 10 percentage point increase in the initial debt to GDP ratio is associated with a slowdown in annual real per capita growth of approximately 20 basis points. The above result should be interpreted with some caution. The difference and system GMM estimators are mainly applicable to micro data and are poorly suitable for macroeconomic datasets with a relatively small number of cross-sectional units (Bond, 2002). In addition, system GMM estimations of the relationship between debt and economic growth are similar to those obtained from OLS regressions. There are two possible interpretations for this result: either public debt is not endogenous or the system GMM estimation does not solve the endogeneity problem.

Checherita-Westphal and Rother (2010) analyze data for 12 Euro-area countries over the period 1970-2008 and instrument the debt to GDP ratio of country *i* and time *t*with the average debt to GDP ratio in the other 11 countries at time *t*. With the above strategy, the study finds a non-linear hump-shaped relationship between debt and growth. Their estimations suggest that growth reaches a maximum when the debt to GDP ratio is between 90 and 100 percent.

The problem with the above instrument used by the authors is two-fold. First, the instrument is only valid if "there is no strong relationship between the debt levels in other euro area countries and the per-capita GDP growth in one specific country". This assumption is not defensible. Second, the instrumental variable approach of the authors yields results that are very close to those of the OLS regressions. This can mean either that debt is not endogenous or that the instrument is not appropriate.

2.2. Relationship between Income Inequality and Economic Growth

There is no consensus in the empirical literature on the relationship between income inequality and economic growth (de Dominicis et al., 2008). Differences in estimation methods, data quality, sample coverage, and the initial level of income are some of the determinants of the relationship between income inequality and economic growth (Castells-Quintina and Royuela, 2012). Most studies are cross-sectional in nature with only a limited number of country-specific studies.

Barro (2000) finds a negative relationship between income inequality and growth for poor countries and a positive relationship for rich countries. Galor and Moav (2004) elaborate on Barro's findings. They argue that while income inequality positively affects economic growth at the stages of physical capital accumulation, this process is reversed at the stages of human capital accumulation. They also found that the long-run relationship between inequality and growth is negative while the short-run effect of inequality on growth is positive.

Alesina and Rodrik (1994) find that higher degree of inequality of wealth and income leads to greater rate of taxation and thus to lower economic growth. In other words, the more unequal distribution of resources leads to lower rate of economic growth, and the link between them is given by redistributive policies. Their empirical results suggest that inequality in land and income is negatively correlated with subsequent economic growth.
Persson and Tabellini (1994) theoretically model the relationship between inequality in income and economic growth. The channel they identify in affecting the above relationship is through decrease in investments. Their empirical results indicate a negative relation between initial income inequality and subsequent economic growth. They assert that the transmission channel of fiscal policy should be examined carefully since government interventions caused by distributional conflicts can lead to a decline in investments and thus lead to a decline in economic growth.

Frank (2009) studies the case of inequality and economic growth in the United States with a new state level panel of income inequality measures for the period 1945-2004. Five measures of income inequality are considered in the study, namely Gini coefficient, top 1 percent share of income, top 10 percent share of income, Theil measure of inequality, and Atkinson measure of inequality. Given the large and balanced size of the panel, the author uses three alternative dynamic panel error correction models, namely the FE estimator, the MG estimator of Pesaran and Smith (1995), and the pooled MG estimator of Pesaran, Shin and Smith (1999). Their results indicate that a two standard deviation increase in the top 10 percent share of income is related to an increase in the long-run growth rate of real income per capita by 0.07 percent. In addition, using several measures of income inequality, this positive relationship is driven mainly by income concentration within the upper end of the income distribution.

The main limitations of the study are two-fold: First, the analysis does not consider the impact of structural breaks in the time series, nor does it consider potential non-linearities in the relationship between income inequality and economic growth. Second, the study also does not consider an appropriate lag interval between measures of income inequality and economic growth. Thus, the short-run and long-run differences cannot be identified from the analysis presented. One of the main channels through which income inequality affects economic growth is fiscal performance, since redistribution policies by the government can have different effects on different segments of the population. We discuss this next.

2.3. Relationship between Income Inequality and Fiscal Performance

Economic recessions accompanied with high inequality can lead to political pressures, which can cause large discretionary spending (Davtyan, 2014). Lower income groups can

demand more transfers while groups with higher incomes want to obtain tax benefits through lower levels of taxation. This redistribution mechanism is influenced by the relative power of each group in the decision making process. In the long-run, such conflicts can lead to excessive debt if the government pays for these transfers to certain groups without taxing others. In the short-run, an economic boom increases government income, making it easier to pay more transfers to all groups, while in a recession the government with lower income prefers to borrow or raise taxes to address these conflicts among groups (Milanovic, 1999). Larch (2012) argues that fiscal performance is influenced by different degrees of income inequality. In particular, the author shows that countries with higher degree of income inequality run large deficits and are prone to accumulate large government debt. The authors' univariate regression model suffers from the problem of endogeneity and causality between dependent and independent variables.

Kourtellos and Tsangarides (2015) uses a Bayesian model averaging method using duration models to examine the relationship between inequality, redistribution, and the duration of growth spells for a sample of 153 countries over the period 1950-2010. The authors control for exogenous shocks, human capital, institutions, socioeconomic factors and unobserved heterogeneity and time effects. The results of the study are as follows: First, lower inequality is strongly and robustly correlated with longer growth spells, while redistribution does not influence the duration of growth spells and its effect is generally not significant. This result may suggest that the inequality growth relationship is not due to the impact of inequality on redistribution, and that the combined direct and indirect effects of redistribution are on average spell preserving. Second, the study finds no evidence of non-linearities in the inequality i.e. redistribution growth spell relationship. Thus, the effect of inequality on growth spell duration does not depend on the extent of inequality while redistributive policies, irrespective of their magnitude are generally not significant for growth spells. The authors' suggest that properly account for model uncertainty is important for decision makers to use findings of growth empirics for policy advice.

In light of the above studies, we present a study of the relationship between income inequality, public debt and economic growth for U.S. states over the period 1987-2011. We use a Bayesian model averaging (BMA) method to account for model uncertainty. We consider a host of covariates, such as measures of human capital, shares of trade in manufacturing and services, and also control for the initial levels of fiscal sustainability. The robust set of covariates substantiates our findings on the relationship between the above variables, while BMA accounts for model uncertainty by taking into account the quantiles of the distribution. We discuss the BMA method in the next section.

3. Bayesian Model Averaging

In a typical economic growth problem[1], a sample data set is of the form $D_n = \{(y_i, x_i)\}_{i=1}{}^{n}$. Here, n is the sample size of the observations, y_i is the ith observation of the dependent variable Y_i corresponding to an observed vector of p observed covariates $x_i = (1, x_{i1}, \ldots, x_{ip})^T$. The constant 1 is included for notational convenience.

A Bayesian regression model is a probability density function $f(y \mid x;\ \varphi)$, that depends conditionally on covariates x and the model parameters denoted by a vector, $\varphi \in \Omega_\varphi$, where $\Omega_\varphi = \{\varphi\}$ is the parameter space. For any given model parameter value $\varphi \in \Omega_\varphi$, the density $f(y_i \mid x_i;\ \varphi)$ is the likelihood of y_i given x_i, and $L(D_n;\ \varphi) = \prod_{i=1}^{n} f(y_i \mid x_i;\ \varphi)$ is the likelihood of the full dataset Dn under the model. A Bayesian regression model is given completely by the specification of a prior distribution $\prod(\varphi)$ over the parameter space Ω_φ, and the corresponding $\pi(\varphi)$ gives the corresponding probability density of a given parameter $\varphi \in \Omega_\varphi$. The posterior distribution according to Bayes' theorem is given by:

$$\boldsymbol{\pi}(\varphi \mid D_n) = \frac{\prod_{i=1}^{n} f(y_i|x_i;\varphi)d\pi(\varphi)}{\int \prod_{i=1}^{n} f(y_i|x_i;\varphi)d\pi(\varphi)} \tag{1}$$

The corresponding posterior predictive cumulative distribution function (c.d.f) ($F(y \mid x)$), mean (expectation, $\mathbb{E}$), variance ($\mathbb{V}$), median, uth quantile ($Q(u \mid x)$) for some chosen $u \in [0,1]$ is given by:

$$F_n(y \mid x) = \int_{Y \le y} f(y \mid x;\ \varphi) d\pi(\varphi \mid D_n) \tag{2a}$$

$$\mathbb{E}_n(y \mid x) = \int y\, d\, F_n(y \mid x) \tag{2b}$$

$$\mathbb{V}_n(y \mid x) = \int \{y - \mathbb{E}_n(y \mid x)\}^2 dF_n(y \mid x) \tag{2c}$$

$$Q_n(u \mid x) = F_n{}^{-1}(u \mid x) \tag{2d}$$

Depending on the choice of posterior predictive functional form in equation (2), a Bayesian regression analysis can provide inferences in terms of how the mean (2b), variance (2c), quantile (2d) for a given choice of $u \in [0,1]$varies as a function of the covariates x.

We use the partial dependence method (Friedman, 2001) to study how the predictions of economic growth (Y) varies as a function of the focal covariates x_s. Let x_s be a focal subset of the covariates $(x_1, \ldots \ldots, x_p)$ with x_s also including the constant term. Let us denote x_c to be the non-focal complement set of q covariates. Then $x_s \cap x_c \neq \emptyset$ and $x = x_s \cup x_c$.

[1] This section will closely follow Karabatsos (2015) in the notations.

In this method, the predictions of Y, conditionally on each value of x_s are averaged over data D_n observations $\{x_{ci}\}_{i=1}^{n}$ and effects of non-focal covariates x_c. The averaged prediction of Y, conditionally on a value of the covariates x_s is given by:

$$F_n(y \mid x_s) = \frac{1}{n}\sum_{i=1}^{n} F_n(y \mid x_s, x_{ci}) \tag{3a}$$

$$\mathbb{E}_n(y \mid x_s) = \frac{1}{n}\sum_{i=1}^{n} E_n(y \mid x_s, x_{ci}) \tag{3b}$$

$$\mathbb{V}_n(y \mid x) = \frac{1}{n}\sum_{i=1}^{n} E_n\{y - \mathbb{E}_n(y \mid x_s, x_{ci})\}^2\} \tag{3c}$$

$$Q_n(u \mid x) = \frac{1}{n}\sum_{i=1}^{n} F_n^{-1}(u \mid x_s, x_{ci}) \tag{3d}$$

The equations above give respectively the posterior c.d.f., mean, variance, quantile at $u \in [0,1]$, conditionally on a value x_s of the focal covariates. The partial dependence method can be computationally demanding as the sample size n, the dimensionality of x_s, and the number of MCMC sampling iterations performed for the estimation of the posterior distribution of the model parameters increases.

The predictive fit of Bayesian regression model to a set of data can be assessed on the basis of posterior predictive expectation (2b) and variance (2c). The proportion of variance explained in the dependent variable Y is measured by the R-squared statistic as follows:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(y_i - \mathbb{E}_n[Y|X_i])^2}{\sum_{i=1}^{n}\{y_i - (\frac{1}{n}\sum_{i=1}^{n} y_i)\}^2}\right) \tag{4}$$

If we want to compare M regression models in terms of predictive fit to the given data setD_n, then for each model, a global measure of predictive fit is given by the mean-squared predictive error as follows:

$$(\underline{m}) = \sum_{i=1}^{n}\{y_i - \mathbb{E}_n(Y \mid x_i, \underline{m})\}^2 + \sum_{i=1}^{n}\mathbb{V}_n(Y \mid x_i, \underline{m}) \tag{5}$$

The first term in equation (5) measures model goodness of fit to the data D_n, and the second term is model penalty. Among a set of M regression models, the model with the best predictive fit for the data D_n is the one with the smallest value of $D(\underline{m})$ (Gelfand and Ghosh, 1998).

3.1. MCMC Methods

A typical Bayesian model does not usually lead to a closed form solution as given by equation (1). Thus, the posterior distribution along with any function of the posterior distribution of interest can be estimated using the Markov Chain Monte Carlo (MCMC) methods (Brooks, 1998). First, a discrete-time Harris ergodic Markov chain $\{\varphi^{(s)}\}_{s=1}^{S}$ with stationary posterior distribution $\prod(\varphi \mid D_n)$ is constructed and ergodicity is ensured by a proper prior density function $\prod(\varphi)$ (Robert and Casella, 2010).

Next, a realization $\varphi^{(s)}$ from the Markov chain is generated by first specifying partitions φ_b ($b=1, \ldots,B$) of the model's parameter φ, and then simulating a sample from each of the full conditional posterior distributions. Then, as $S \to \infty$, the MCMC chain $\{\varphi^{(s)}\}_{s=1}^{S}$ converges to samples from the posterior distribution $\prod(\varphi \mid D_n)$. The goal is to construct a MCMC chain for a sufficiently large finite S (Karabatsos, 2015).

The MCMC convergence analysis is used to check whether a sufficiently large number of sampling iterations has been run to ensure that the resulting samples $(\{\varphi^{(s)}\}_{s=1}^{S})$ have converged to samples from the model's posterior distribution. The MCMC convergence can be examined in two steps: First, for each of these model parameters, the univariate trace plot of parameter samples over the MCMC sampling iterations can be examined. This step is done to evaluate whether "good mixing" is achieved that appears stable and hairy over MCMC iterations (Brooks, 1998). Second, for each model parameter of interest, a sub-sampling analysis of the MCMC samples are done in order to compute the 95% Monte Carlo Confidence Intervals (MCCI) of posterior point-estimates of interests, such as marginal posterior means, variances, quantiles of the posterior distribution.

For a given marginal posterior point estimate of a parameter, the 95% MCCI half-width size measures the imprecision of the estimate due to Monte Carlo sampling error. The half-width becomes smaller as the number of MCMC sampling iterations increases. MCMC convergence is achieved by adequate MCMC mixing and small 95% MCCIs half-widths for the posterior point estimates of parameters of interest. It is important to achieve adequate convergence if initially the MCMC sampling run does not generate convergence (Karabatsos, 2015). We next turn to describing the dataset used in the study.

3.2. Data and Measurement of Variables

Our data covers the period 1987-2011. The choice of this period is motivated by the fact that public debt to GDP ratio increased significantly for many states, as well as the observation that income inequality (both household level measures and national level measures) increased over this time period. We have a panel dataset with 1200 observations i.e. 50 states with 24 years of data.

Our dependent variable in the model is the per-capita GDP growth rate. This variable is measured as the percentage change from the previous period.

3.3. Independent Variables

Our main independent variable is the public debt to GDP ratio for states. This information is obtained from the National Governors Association historical data on Fiscal Survey of States (http://www.nasbo.org/publications-data/fiscal-survey-of-the-states). We also consider five different measures of income inequality, namely the proportion of the total

income received by the top 1 percent, the proportion of the total income received by the top 10 percent in the percentile rankings of income distribution. The above two data sets are computed by Frank (2014) using the IRS income data.

In computing the Gini index, a compromise measure is constructed using the method of Cowell (1995). The lower limit of the gini is derived based on the assumption that all individuals in a group receive exactly the mean income of the group. Similarly, the upper limit gini is constructed based on the assumption that individuals within the group receive income equal to either the lower or the upper bound of the group interval. The Atkinson index and Theil entropy index are constructed using the split-histogram density and an evaluation function. [2] Unlike the percentile rankings or gini index, the Atkinson index and Theil index are undefined for negative incomes (Cowell, 1995). Thus, to construct these indices, negative IRS income data was truncated, meaning the lowest possible income is zero.

In constructing the human capital measures, the perpetual inventory method of Barroand Lee (2000) is used (Frank, 2014).[3] Attainment information from the Census and the March CPS is used as benchmark human capital stocks, while the number of new graduates each year is used as flows that are added to the current stock of human capital. Additionally, each year's stock is adjusted for mortality and net migration. Two measures of human capital measures are constructed by Frank (2014), namely the high school human capital stock and the college attainment human capital stock.

The assumption behind the construction of these measures is that the number of deaths and net migration are independent from the level of schooling attained. Though this is not quite an accurate assumption, such an assumption is necessary given the data limitations.
In evaluating the accuracy of the perpetual inventory method, the attainment data for the period 1979-2010 is compared using the Census benchmark information and then these values are compared to the actual attainment information provided in the March CPS data. The root mean square error of the actual and estimated values is 0.022 for high school attainment and 0.013 for college attainment. Furthermore, the Theil *U* statistic is used (a measure between 0 and 1) to assess forecasting performance. Higher values of Theil *U* statistic denote poor forecasting performance. Over this period, the Theil *U* statistic for high school attainment was 0.043. Similarly, the Theil *U* statistic for college attainment is 0.087. Both values indicate that the two attainment measures provide a good fit for the sample period, though the high school attainment measure performs better than the college attainment measure.

[2] The details of construction of these indices can be found in Frank (2009).
[3] The dataset can be found at: http://www.shsu.edu/eco_mwf/inequality.html

We also consider an additional number of covariates in the model. First, the employment to population ratio is considered for each state from the Bureau of Labor Statistics data. This measure is considered, since higher employment to population ratio is likely to lead to higher per-capita GDP growth rate from the supply side. Also, higher employment to population ratio is likely to lead to higher tax revenues, which is likely to reduce public debt to GDP ratio and thus may boost higher per-capita GDP growth indirectly.

Next, we consider the export intensity of each state's exports in the manufacturing sector to 8 different regions in the world, namely Sub-Saharan Africa, South America, Oceania, North America, Middle East, North Africa, Europe and Asia. This information was only available for the period 1999-2014 and thus when we include these observations in the data we lose a lot of degrees of freedom in the data. [4] The Export intensity of each state to each geographic region is defined as follows:

$$\text{Export Intensity of Manufacturing in a given region } d = \frac{\sum X_{md} / \sum X_{m\ world}}{\sum X_{total\ \ d} / \sum X_{total\ \ world}} \quad (6)$$

The above definition is compatible with the United Nations Commodity trade data. The definition states that any state's export intensity of manufacturing to a given region *d* is the ratio of its manufacturing sector exports to the total manufacturing sector exports to the world to the ratio of its total exports to a given region *d* to the total exports to the world. This ratio can be greater than 1 if the manufacturing share of exports of a given state to a given destination is much higher than its share of total exports to a given destination. As there has been increasing debate in the policy and trade community of whether jobs are being lost as a result of trade with partner countries, considering this measure as a covariate is important to understand how export intensity is affecting the per-capita GDP growth of a given state, through both the direct channel of national incomes and through the indirect fiscal channels of state's revenues.

As our variables are measured in different economic units, we scale all our variables to a mean of zero and standard deviation of one in order to ensure comparability and consistency of the effect of the independent variables on our dependent variable. This will tell us how the standardized measure of our independent variables in the model affects the standardized per-capita GDP growth rate.

4. Empirical Results

In this section, we first present our baseline results using the least squares regression model. In sub-section 2, we use different models using Dirichlet process mixture of homoscedastic linear regression model (DPHLM), the Pitman-Yor (PY) process mixture

[4] This information was obtained from: http://tse.export.gov/tse/MapDisplay.aspx

of homoscedastic linear regression model, the NIG process mixture of linear regression model (NIGLR), and the Normal Random Effect Bayesian Model (NREM). We conclude this section by demonstrating that the normal random effect model (2-level) outperforms all the other models in terms of goodness of fit. Thus, we have 4 different classes of model with five different measures of inequality as independent variables. We also describe the values assumed for the prior parameters of the Bayesian models considered. As a baseline case, we first fit a Bayesian normal linear regression model introduced by Lindley and Smith (1972). This model is of the following form:

$$\begin{aligned}
&y_i \mid x_i \sim f(y \mid x_i),\ i = 1, \dots\dots, n \\
&f(y \mid x) = n(y \mid x\beta, \sigma^2) \\
&\beta_0 \mid \sigma^2 \sim N(0, \sigma^2 v_{\beta 0} \to \infty) \\
&\beta_k \mid \sigma^2 \sim N\left(0, \sigma^2 v_\beta\right),\ k = 1, \dots., p \\
&\sigma^2 \sim IG({}^{a_0}/_2, {}^{a_0}/_2)
\end{aligned} \tag{7}$$

We assume the following values for a_0 and v_β, namely $a_0 = 0.001$ and $v_\beta = 1000$. The posterior summary estimates of the parameters of the model (the first quartile, median and the third quartile values) along with the CUSUM values are reported in Table 1.[5]

Table 1 reports the median, first quartile, and third quartile estimates of the parameters in the model. As evident from this table, higher income share of the top 1 percent unambiguously reduces per-capita GDP growth rates possibly due to the fact that lower social mobility and lower tax revenues affects the fiscal situations of state governments negatively, which has an adverse impact on per-capita GDP growth rate. The estimated Z-score coefficients vary between -0.17 and -0.1 for the first and third quartiles of the income distribution. Similarly, higher debt to income ratio also lowers the per-capita GDP growth rate as state governments are unable to undertake necessary investments in infrastructure and R&D investments that are conducive to productive expenditures. The estimated Z-score coefficients vary between -0.5 and -0.35 for the first and third quartiles of the income distribution. The coefficient of the product of public debt to GDP ratio and income inequality measure has a positive effect on per-capita GDP growth rate. Does this suggest that there is a role of public policy in terms of higher government expenditures in the short-run? We suggest that this may be the case later in this paper and the rationale of why cutting public expenditures at least in the short-run may not be productive as suggested by austerity advocates.

[5] For all tables of parameter estimates, the results are based on 39600 Monte Carlo samples out of a total of 200000 samples that were generated. We do not report all the other parameters in the model due to lack of space. These results can be obtained from the authors' upon request. CUSUM denotes cumulative sum control chart and CUSUM = ½ indicates optimal MC mixing of parameters.

Table 1: Linear Regression Model Posterior Estimates of Public Debt to GDP ratio and Income inequality (top 1 % income share) on Per-Capita GDP Growth rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.000	-0.018	0.018	0.505
Income share of top 1 percent	-0.137	-0.173	-0.102	0.499
Debt to Income ratio	-0.428	-0.505	-0.351	0.499
Product of Debt and Inequality	0.418	0.333	0.505	0.499
Educational attainment high school	-0.058	-0.088	-0.030	0.502
Educational attainment college	-0.102	-0.133	-0.070	0.497
Employment to population ratio	0.118	0.094	0.142	0.498
Export intensity – Sub-saharan Africa	-0.086	-0.111	-0.061	0.502
Export intensity- South America	0.023	-0.007	0.054	0.502
Export intensity- Oceania	-0.011	-0.033	0.010	0.500
Export intensity- North America	0.175	0.147	0.204	0.503
Export intensity- Middle East	-0.282	-0.321	-0.243	0.500
Export intensity- North Africa	0.006	-0.021	0.034	0.501
Export intensity- Europe	0.220	0.192	0.249	0.495
Export Intensity- Asia	0.168	0.141	0.195	0.501
Reserves to expenditure ratio	0.095	0.071	0.119	0.497
Model posterior predictive SSE	2160.94			
R squared	0.106			

Educational attainment of high school and college graduates have unambiguous negative effect on per-capita GDP growth rate suggesting that there is room for improving public education both in the short-run and the long-run in order to reverse this situation. The employment to population ratio coefficient is positive, suggesting that higher employment to population ratio generates higher tax revenues, which reduces public debt and thus have a positive impact on per-capita GDP growth rate.

The coefficients on manufacturing export intensity have different effects on per-capita GDP growth rate depending on the region under study. For example, exporting manufacturing goods to the sub-saharan Africa and Middle Eastern region have a negative effect on per-capita GDP growth rate. This result may be due to the fact that sub-saharan

Africa's manufacturing capacity is already quite low. On the other hand, the Middle-East specializes only in oil and natural gas production. Thus, manufacturing capacity in this region is not well diversified in productive capacity suggesting that exports of manufacturing inputs that focus only in oil and natural gas production is relevant to this region. In contrast, exporting manufacturing goods to North America, Europe and Asia has a positive effect on per-capita GDP growth rate. This may be due to the NAFTA agreement in the North American region, where trade is taking place at a higher rate than other regions. In Europe and Asia, many multinational enterprises of U.S. firms has set up production and R&D facilities and thus there is scope for vertical integration and knowledge spillovers between local subsidiaries and U.S. MNEs. Thus, manufacturing export intensity has a positive and significant effect on per-capita GDP growth rate for these regions.

Figure 1: Marginal Posterior Distribution of the Independent Variables for a Linear Regression Model with Income Share of the top 1% as one Regressor

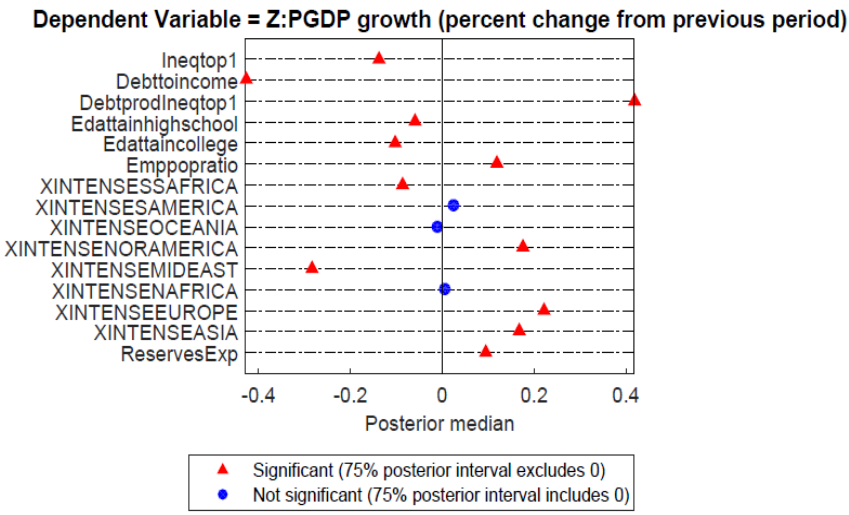


Figure 1 corroborates the above results using the marginal posterior distribution of the posterior median. The results show the significance of the independent variables at the 75% posterior intervals that exclude zero. Figure 2 and 3 show the conditional distributions of income inequality and debt to income ratio on per-capita GDP growth rates holding the other variable constant. From Figure 2, we can infer that higher income inequality has a negative effect on per capita GDP growth at higher levels of debt to income ratio. Similarly, from Figure 3 we can infer that higher debt to GDP ratio has a negative effect on per-capita GDP growth rate at higher levels of income inequality. These results are intuitive and corroborate with findings of other researchers (Stiglitz, 2015).

Figure 2: Conditional Distributions of Income Inequality (top 1% income share) on Per-Capita GDP Growth Rates Assuming Different Values of Debt to GDP Ratio

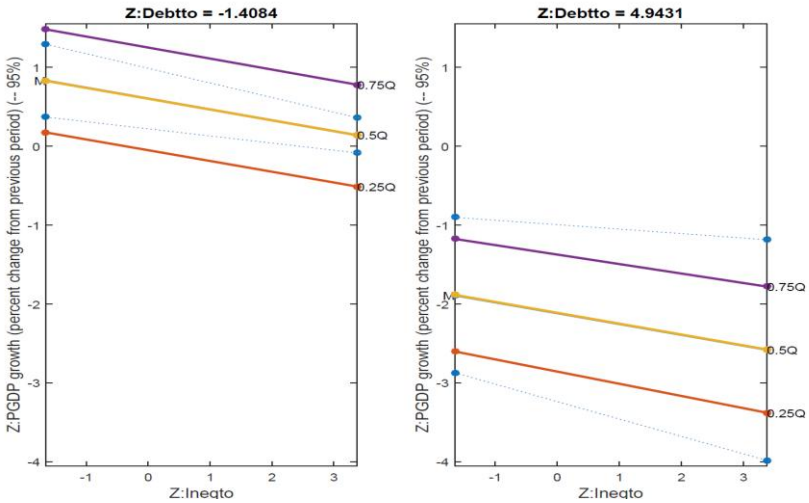
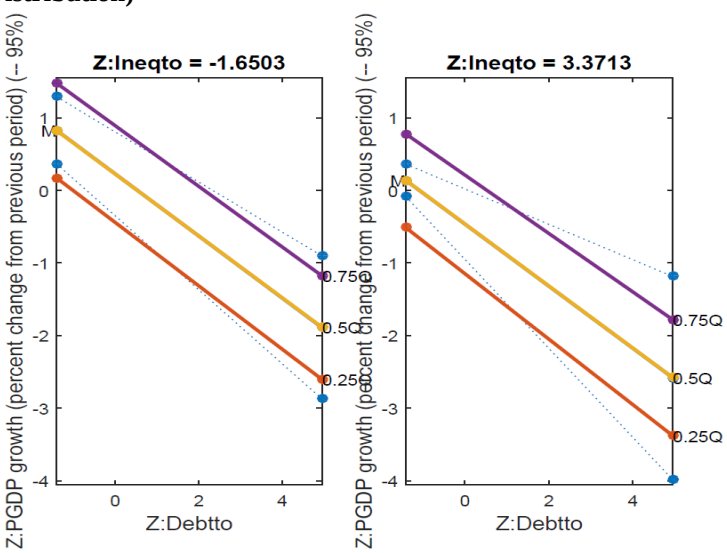


Figure 3: Conditional Distributions of Debt to GDP Ratio on Per-Capita GDP Growth Rates Assuming Different Values of Income Inequality (Share of Top 1 % in Income Distribution)



Source: Authors' own computations.

Table 2: Linear Regression Model Posterior Estimates of Public Debt to GDP Ratio and Income inequality (Income Share of Top 10 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.000	-0.018	0.018	0.505
Income share of top 10 percent	-0.103	-0.140	-0.066	0.499
Debt to Income ratio	-0.810	-0.995	-0.624	0.498
Product of Debt and Inequality	0.784	0.590	0.981	0.499
Educational attainment high school	-0.068	-0.096	-0.040	0.501
Educational attainment college	-0.100	-0.134	-0.067	0.496
Employment to population ratio	0.112	0.087	0.135	0.499
Export intensity-Sub-Saharan Africa	-0.082	-0.107	-0.057	0.501
Export intensity- South America	0.020	-0.010	0.051	0.503
Export intensity- Oceania	-0.012	-0.034	0.009	0.500
Export intensity- North America	0.176	0.148	0.206	0.503
Export intensity- Middle East	-0.282	-0.321	-0.243	0.501
Export intensity- North Africa	0.003	-0.025	0.031	0.501
Export intensity- Europe	0.231	0.203	0.260	0.494
Export Intensity- Asia	0.173	0.146	0.200	0.501
Reserves to expenditure ratio	0.092	0.068	0.116	0.497
Model posterior predictive SSE	2166.590			
R squared	0.104			

Table 2 reports the median, first quartile, and third quartile estimates of the parameters in the model. As evident from this table, higher income share of the top 10 percent unambiguously reduces per-capita GDP growth rates possibly due to the reasons as cited in the previous table. The estimated Z-score coefficients vary between -0.14 and -0.06 for the first and third quartiles of the income distribution. The qualitative results remain unchanged as explained in the previous table and graphs. Overall, our fit to the model is poor (an R square value of only 0.104). As this is a baseline model, we will later improve upon this baseline model using other priors in the next section of the paper. Figure 4, 5 6 and 7 show marginal posterior distribution of the independent variables, conditional distributions of income inequality and conditional distributions of debt to GDP ratio on

per-capita GDP growth rates and marginal posterior distribution of the independent variables respectively. Figure 8 and 9 exhibit conditional distributions of income inequality (Theil t statistic) on per-capita GDP growth rates and conditional distributions of debt to GDP ratio on per-capita GDP growth rates

Figure 4: Marginal Posterior Distribution of the Independent Variables for a Linear Regression Model with Income Share of the top 10% as one Regressor

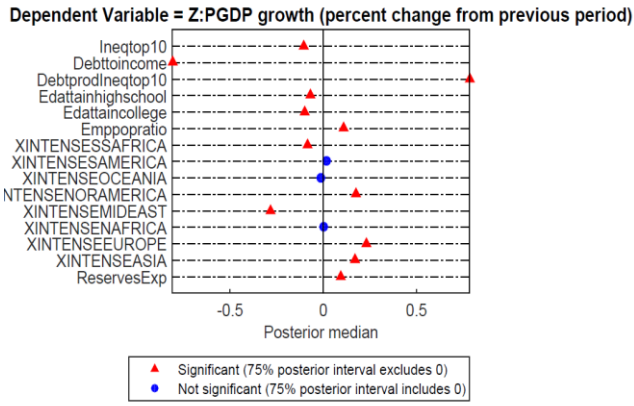


Figure 5: Conditional Distributions of Income Inequality (Top 10% Income Share) on Per-Capita GDP Growth Rates Assuming Different Values of Debt to GDP Ratio

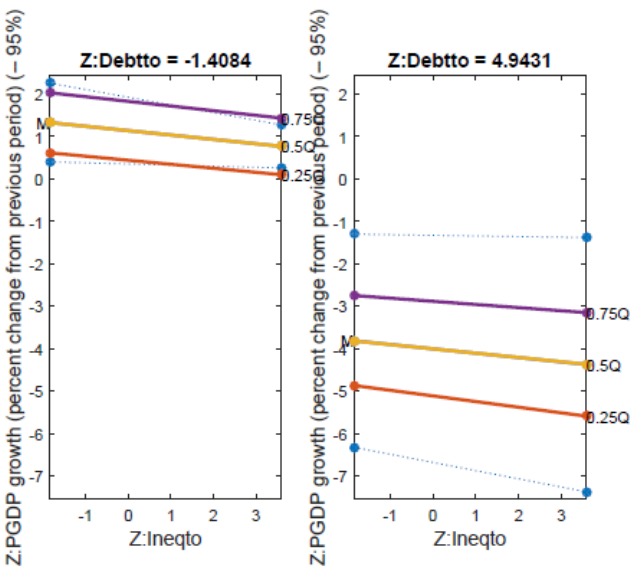
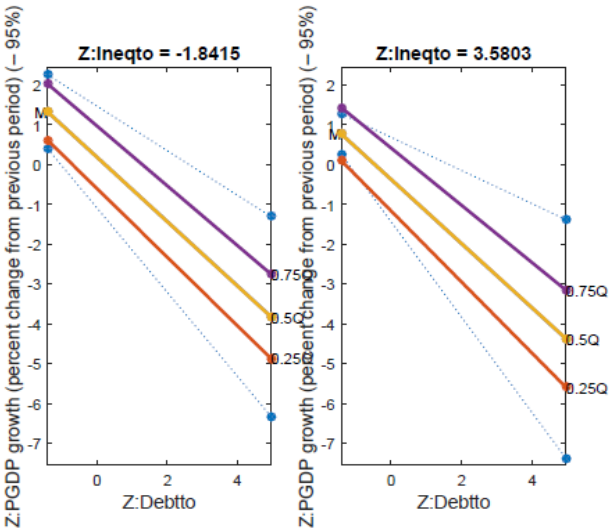


Figure 6: Conditional Distributions of Debt to GDP ratio on Per-Capita GDP Growth Rates Assuming Different Values of Income Inequality (Share of Top 10 % in income distribution)



Source: Authors' own computations.

Figure 7: Marginal Posterior Distribution of the Independent Variables for a Linear Regression Model with Theil T Statistic as one Regressor

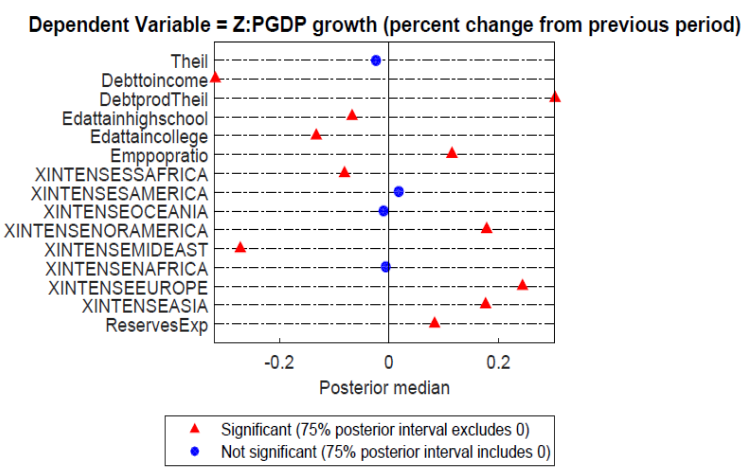


Figure 8: Conditional Distributions of Income Inequality (Theil T Statistic) on Per-Capita GDP Growth Rates Assuming Different Values of Debt to GDP Ratio

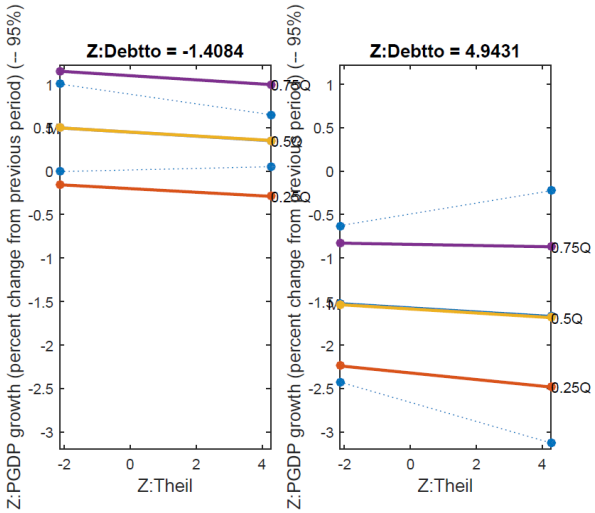
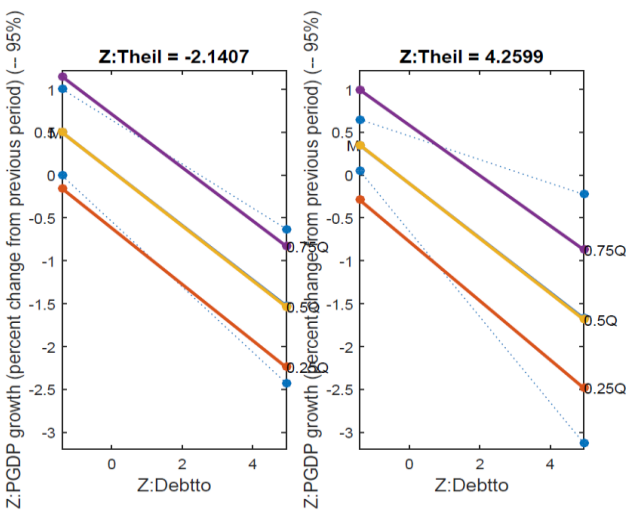


Figure 9: Conditional Distributions of Debt to GDP Ratio on Per-Capita GDP Growth Rates Assuming Different Values of Income Inequality (Theil T Statistic)



Source: Authors' own computations.

Table 3: Linear Regression Model Posterior Estimates of Public Debt to GDP Ratio and Income inequality (Theil index) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.000	-0.019	0.018	0.499
Theil T statistic	-0.023	-0.060	0.014	0.496
Debt to Income ratio	-0.318	-0.393	-0.243	0.500
Product of Debt and Inequality	0.302	0.215	0.390	0.499
Educational attainment high school	-0.067	-0.095	-0.039	0.500
Educational attainment college	-0.134	-0.167	-0.101	0.505
Employment to population ratio	0.115	0.091	0.138	0.500
Export intensity – Sub-saharan Africa	-0.082	-0.107	-0.057	0.498
Export intensity- South America	0.019	-0.011	0.049	0.504
Export intensity- Oceania	-0.010	-0.031	0.011	0.498
Export intensity- North America	0.178	0.149	0.208	0.501
Export intensity- Middle East	-0.271	-0.310	-0.232	0.498
Export intensity- North Africa	-0.006	-0.034	0.022	0.500
Export intensity- Europe	0.243	0.214	0.271	0.500
Export Intensity- Asia	0.177	0.150	0.204	0.504
Reserves to expenditure ratio	0.084	0.060	0.108	0.502
Model posterior predictive SSE	2158.630			
R squared	0.107			

Table 3 reports the median, first quartile, and third quartile estimates of the parameters. As evident from this table, Theil T statistic unambiguously reduces per-capita GDP growth rates. However, this coefficient is not significant as evident from figure 7. The Theil T statistic lacks an intuitive interpretation as it involves more than a simple difference or ratio. However, Theil's T statistic can incorporate group-level data and is particularly effective at parsing effects in hierarchical data sets. The Theil's T statistic is as follows:

$$T = \sum_{p=1}^{n} \left\{ \left(\frac{1}{n} \right) \right\} * \left(\frac{y_p}{\mu_y} \right) * ln \left(\frac{y_p}{\mu_y} \right) \quad (8)$$

Where, n is the number of individuals in the population, y_p is the income of the person indexed by p, and μ_y is the population's average income. Equation (8) emphasizes the

following main points. First, the summation sign emphasizes the idea that each person will contribute to a Theil element. Second, $\frac{y_p}{\mu_y}$ is the proportion of the individual's income to average income. Third, the natural logarithm of $\frac{y_p}{\mu_y}$ determines whether the element will be positive or negative or zero. The advantage of the Theil index is two-fold: First, it can effectively use group data. Second, it allows the researcher to parse inequality into within group and between group components. The main disadvantages of the Theil Index are (a) It has no intuitive interpretation; and (b) It cannot directly compare populations with different sizes or group structures. Figure 9 again shows that for a given value of Theil T-statistic, higher levels of debt to GDP ratio have more significant and negative impact on per-capita GDP growth.

Table 4: Linear Regression Model Posterior Estimates of Public Debt to GDP Ratio and Income inequality (Gini Coefficient) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.000	-0.018	0.018	0.505
Gini Coefficient	-0.250	-0.287	-0.214	0.499
Debt to Income ratio	-1.008	-1.316	-0.700	0.499
Product of Debt and Inequality	0.946	0.632	1.261	0.497
Educational attainment high school	-0.060	-0.087	-0.032	0.501
Educational attainment college	-0.035	-0.067	-0.004	0.499
Employment to population ratio	0.055	0.031	0.078	0.499
Export intensity – Sub-saharan Africa	-0.094	-0.119	-0.070	0.501
Export intensity- South America	0.030	0.000	0.061	0.504
Export intensity- Oceania	-0.001	-0.022	0.020	0.500
Export intensity- North America	0.161	0.133	0.190	0.503
Export intensity- Middle East	-0.295	-0.333	-0.256	0.500
Export intensity- North Africa	0.022	-0.006	0.049	0.501
Export intensity- Europe	0.223	0.196	0.251	0.495
Export Intensity- Asia	0.166	0.139	0.192	0.501
Reserves to expenditure ratio	0.110	0.086	0.134	0.498
Model posterior predictive SSE	2121.50			
R squared	0.123			

Table 4 reports the median, first quartile, and third quartile estimates of the parameters in the model. As evident from this table, the Gini coefficient unambiguously reduces per-capita GDP growth rates. This coefficient is also significant as evident from Figure 10. The estimated Z-score coefficient varies between -0.29 and -0.21 for the first and third quartiles of the income distribution. The interesting part of this table is a one-to-one negative relationship between debt to income ratio and per-capita GDP growth for the median estimate. This may suggest that as debt to income ratio (z value) increases by one standard deviation unit, the per-capita GDP growth may decrease by one standard deviation unit. In addition, the product of debt to income ratio and Gini coefficient has almost an effect of 0.95 in standard deviation units.

Figure 10: Marginal Posterior Distribution of the Independent Variables for a Linear Regression Model with Gini Coefficient as one Regressor

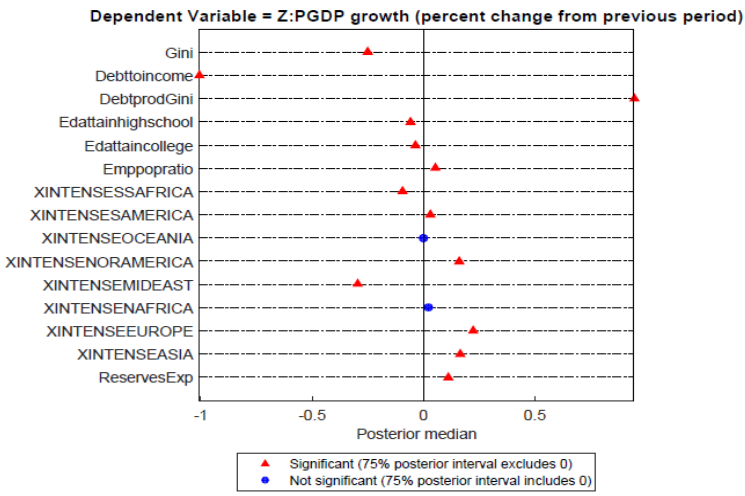


Figure 11 and 12 show conditional distributions of income inequality (Gini coefficient) on per-capita GDP growth rates assuming different values of debt to GDP ratio, and debt to GDP ratio on per-capita GDP growth rates assuming different values of income inequality (Gini coefficient) respectively while Figure 13 shows marginal posterior distribution of the independent variables for a linear regression model with Atkinson measure of inequality as one regressor. Figure 14 and 15 portray conditional distributions of income inequality (Atkinson measure) on per-capita GDP growth rates assuming different Debt to GDP ratio and debt to GDP ratio on per-capita GDP growth rates assuming different values of income inequality (Atkinson measure).

Figure 11: Conditional Distributions of Income Inequality (Gini Coefficient) on Per-Capita GDP Growth Rates Assuming Different Values of Debt to GDP Ratio

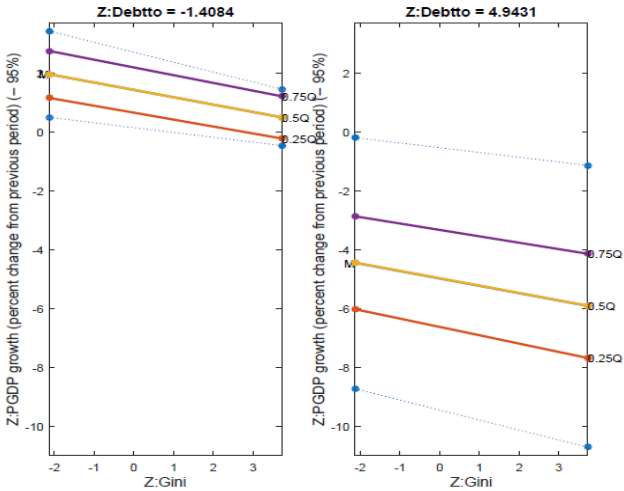
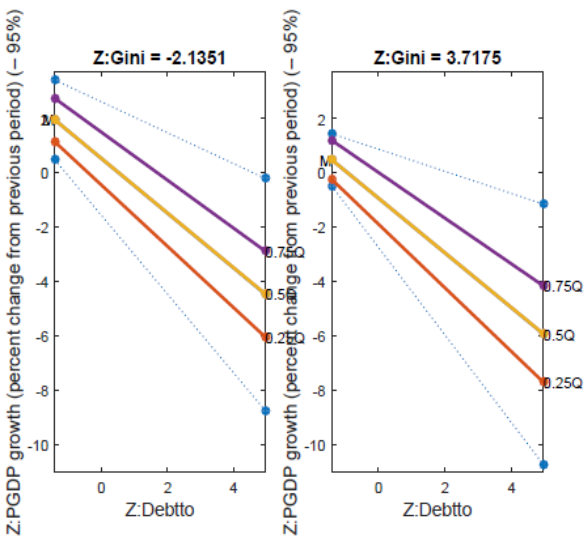


Figure 12: Conditional Distributions of Debt to GDP ratio on Per-Capita GDP Growth Rates Assuming Different Values of Income Inequality (Gini Coefficient)



Source: Authors' own computations

Table 5: Linear Regression Model Posterior Estimates of Public Debt to GDP Ratio and Income inequality (Atkinson Measure) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.000	-0.018	0.018	0.505
Atkinson Measure	-0.043	-0.082	-0.005	0.499
Debt to Income ratio	-0.480	-0.600	-0.359	0.499
Product of Debt and Inequality	0.456	0.326	0.590	0.498
Educational attainment high school	-0.071	-0.099	-0.043	0.501
Educational attainment college	-0.124	-0.159	-0.090	0.498
Employment to population ratio	0.116	0.092	0.139	0.498
Export intensity – Sub-Saharan Africa	-0.083	-0.108	-0.058	0.501
Export intensity- South America	0.020	-0.010	0.050	0.503
Export intensity- Oceania	-0.011	-0.032	0.010	0.501
Export intensity- North America	0.175	0.146	0.204	0.503
Export intensity- Middle East	-0.278	-0.316	-0.239	0.501
Export intensity- North Africa	-0.002	-0.029	0.026	0.501
Export intensity- Europe	0.237	0.209	0.266	0.495
Export Intensity- Asia	0.176	0.150	0.203	0.502
Reserves to expenditure ratio	0.085	0.061	0.109	0.498
Model posterior predictive SSE	2164.94			
R squared	0.105			

Table 5 reports the median, first quartile, and third quartile estimates of the parameters in the model. As evident from the marginal posterior distribution, the Atkinson measure has a negative and significant effect on per-capita GDP growth holding other variables in the model constant. The estimated Z-score coefficient varies between -0.08 and -0.005 for the first and third quartiles of the distribution.

Figure 13: Marginal Posterior Distribution of the Independent Variables for a Linear Regression Model with Atkinson measure of inequality as one Regressor

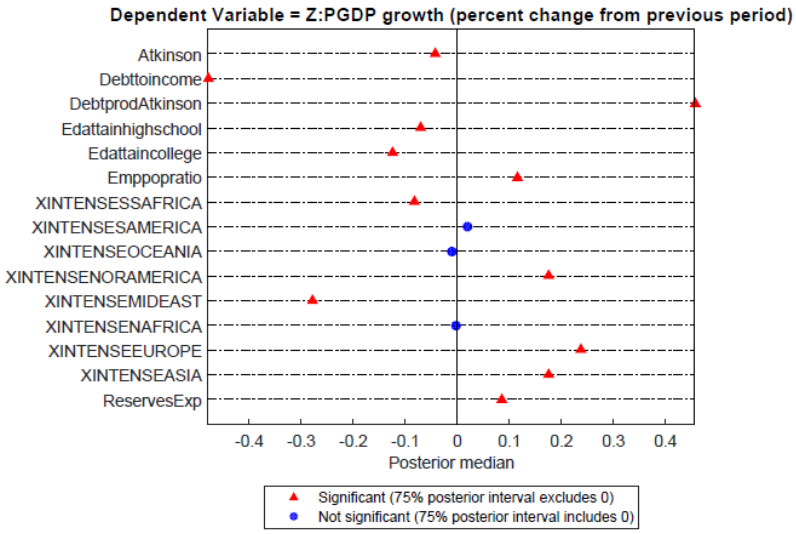


Figure 14: Conditional Distributions of Income Inequality (Atkinson Measure) on Per-Capita GDP Growth Rates Assuming Different Debt to GDP Ratio Values

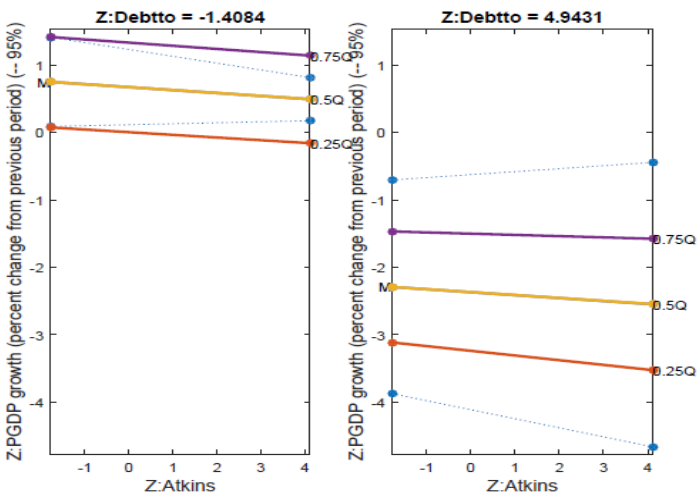
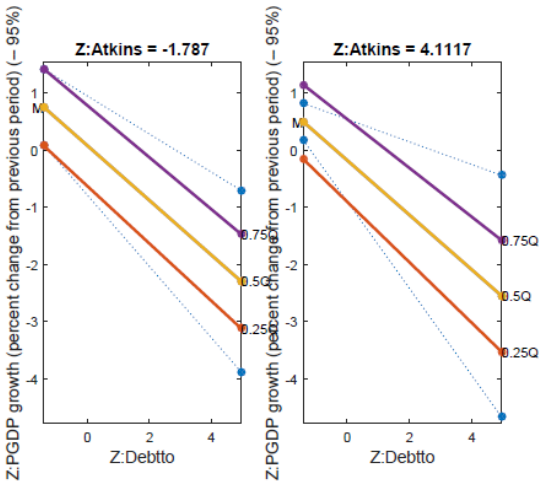


Figure 15: Conditional Distributions of Debt to GDP ratio on Per-Capita GDP Growth Rates Assuming Different Values of Income Inequality (Atkinson Measure)



Source: Authors' own computations.

The Atkinson measure may be defined as follows: Suppose that there are a finite number of income groups of M with N_i individuals at each level. Let $\gamma \geq 0$ be a parameter that denotes aversion to inequality among different groups of income levels of after-tax incomes:

$$\omega = \left[\sum_{i=1}^{M} \sum_{j=1}^{N_i} (y_i - T_{ij})^{(1-\gamma)}\right]^{\frac{1}{(1-\gamma)}} \tag{9}$$

Where, y_i is the before-tax income of individuals in group i and T_{ij} is the tax payment by the jth individual in group i. The higher is γ, the more averse to inequality the social welfare function in (9) will be. At one extreme, with $\gamma = 0$, the welfare function is the sum of individual incomes — there is no aversion to inequality. On the other hand, for $\gamma = \infty$, society adopt the Rawlsian perspective that places weight on the individual with the lowest income level.

Equation (9) has two important properties. First, it is increasing in each person's after-tax income. Second, for $\gamma \geq 0$, it is increasing with respect to any experiment that shifts income from an individual with after-tax income to one with lower after-tax income. Thus, it simultaneously incorporates notions of vertical equity i.e. redistribution from the rich to the poor and of horizontal equity i.e. a wish to keep after-tax income equal for those with the same before-tax income. This property is clearly an advantage over the Gini coefficient since both vertical and horizontal equities are addressed. We also find from the conditional distributions, that Atkinson measure have a negative effect on per-capita GDP

growth after holding debt to GDP ratio constant. Similarly, the debt to GDP ratio also has a negative effect on per-capita GDP growth holding the Atkinson measure constant.

4.1. Extension of the Baseline Model and Results

Two disadvantages of the baseline least squares regression model are as follows: First, the goodness of fit measure is really low. Second, we also find that both the educational attainment measures come up with a negative sign, which may not correspond to reality. In other words, we do not know how to account for both high school educational attainment and college attainment to have negative effect on per-capita GDP growth in the model. Thus, it is necessary to incorporate different Bayesian priors to address the above issues.

We use different Bayesian priors such as Dirichlet process mixture of homoscedastic linear regression model (DPHLM), the Pitman-Yor(PY) process mixture of homoscedastic linear regression model (PYHLM), the NIG process mixture of linear regression model (NIGLR), and the Normal Random Effect (2-level) Bayesian Model (NREM). We conclude this section by demonstrating that the normal random effect model (2-level) (NRE) outperforms all the other models in terms of goodness of fit. We only report the DPHLM estimates and the NREM models for the sake of brevity. The PYHLM and NIGLR models are given in appendix A, and the results of these models can be obtained from the authors upon request.

DPHLM Priors

Following Karabatsos and Walker (2012b), a multivariate regression model and the associated MCMC estimation methods of the model's posterior distribution is specified as follows:

$$
\begin{aligned}
&(y_{i(h)})_{i(h)=1}^{n_h} | X_h \sim f(\, y_h \mid X_h\,),\ \ h = 1, \dots \dots, N_h \\
&f(\, y_h \mid X_h\,) = \sum_{j=1}^{\infty} \left\{ \prod_{i(h)=1}^{n_h} n(y_{i(h)} \mid x_{i(h)}\beta_j, \sigma^2) \right\} \omega_j \\
&\omega_j = v_j \prod_{l=1}^{j-1} (1 - v_l) \\
&v_j | \alpha = Be(1, \alpha) \\
&\beta_j \mid \mu, T \sim N(\mu, T) \\
&\sigma^2 \sim IG({}^{a_0}/_{2}, {}^{a_0}/_{2}) \\
&\mu, T \sim N(\, \mu \mid 0, r_0 I_{p+1}\,) IW(T \mid p+3, s_0 I_{p+1}) \\
&\alpha \sim Ga(a_\alpha, b_\alpha\,) \qquad (10)
\end{aligned}
$$

In the above equation system, h indicates a group (at level 2), n_h is the number of observations in group h, and N_h denotes the total number of groups. The results of each regression with three different inequality measures are reported below. The values of the priors assumed are as follows: $r_0 = 10;\ s_0 = 10; a_0 = 5; a_\alpha = 1; b_\alpha = 1$.

Table 6: DPHLM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Income share of top 1 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.018	-0.185	0.148	0.420
Income share of top 1 percent	-0.178	-0.333	-0.029	0.420
Debt to Income ratio	-0.410	-0.650	-0.181	0.373
Product of Debt and Inequality	0.400	0.151	0.659	0.369
Educational attainment high school	0.052	-0.103	0.209	0.412
Educational attainment college	-0.078	-0.244	0.086	0.420
Employment to population ratio	0.074	-0.078	0.225	0.430
Export intensity – Sub-saharan Africa	-0.273	-0.447	-0.103	0.402
Export intensity- South America	-0.164	-0.353	0.026	0.410
Export intensity- Oceania	0.118	-0.033	0.269	0.429
Export intensity- North America	0.190	0.016	0.366	0.407
Export intensity- Middle East	-0.548	-0.759	-0.285	0.321
Export intensity- North Africa	0.016	-0.196	0.219	0.366
Export intensity- Europe	0.417	0.244	0.587	0.405
Export Intensity- Asia	0.097	-0.069	0.262	0.420
Model posterior predictive SSE	2084.36			
R squared	0.397			

Table 6 reports the DPHLM estimates for the median, first quartile, and the third quartile of the model. Both the top 1 percent income share and debt to income ratio has a negative effect on per-capita GDP growth rate. The estimated Z-score coefficients for the top 1 percent income share varies between -0.33 and -0.02 for the first and the third quartiles, while the estimated Z-score coefficients for the debt to income ratio varies between -0.65 and 0.18 for the first and third quartiles respectively. In this example, the model fit improves significantly compared to the least squares model. In addition, we also find the

product of the coefficient of debt to income ratio and the top 1 percent income share in the population is positive and significant.

In addition, from examining the conditional distributions of income inequality on per-capita GDP growth, we find that the top 1 percent income share has negative effect. Similarly, from looking at the conditional distribution of debt to income ratio, we find that for the third quartile, debt has a positive effect on per-capita GDP growth when income inequality is high.[6]

Table 7: DPHLM Posterior Estimates of Public Debt to GDP ratio and Income Inequality (Income Share of Top 10 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.051	-0.229	0.126	0.428
Income share of top 10percent	-0.167	-0.335	0.002	0.443
Debt to Income ratio	-0.366	-0.733	-0.066	0.331
Product of Debt and Inequality	0.258	-0.068	0.682	0.292
Educational attainment high school	0.008	-0.159	0.176	0.431
Educational attainment college	0.036	-0.152	0.226	0.400
Employment to population ratio	0.105	-0.054	0.263	0.453
Export intensity – Sub-saharan Africa	-0.376	-0.572	-0.179	0.415
Export intensity- South America	-0.200	-0.399	0.004	0.416
Export intensity- Oceania	0.082	-0.115	0.275	0.376
Export intensity- North America	0.247	0.048	0.452	0.396
Export intensity- Middle East	-0.415	-0.645	-0.183	0.414
Export intensity- North Africa	0.396	0.150	0.631	0.362
Export intensity- Europe	0.306	0.120	0.495	0.424
Export Intensity- Asia	0.204	0.009	0.393	0.405
Model posterior predictive SSE	2226.88			
R squared	0.391			

[6] One rationale for this result may be due to "debt augmenting economic growth". Under a debt-led regime, a rise in the interest rate or debt stimulates effective demand through an increase in capitalist consumption. The interest rate increases one-for-one with a rise in the inflation rate. Thus, economic growth increases with a rise in inflation rate and the interest rate (Nishi, 2012).

Table 7 reports the DPHLM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the income share of the top 10 percent of the population by income levels. In this case, we find that both debt to GDP ratio and income inequality has negative and significant effect on per-capita GDP growth rates. While educational attainment in high school has a marginal positive coefficient, this coefficient is not significant. The other results regarding the manufacturing export intensity also holds true as in table 5.

Table 8: DPHLM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Gini Coefficient) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.004	-0.177	-0.521	0.429
Gini Coefficient	-0.125	-0.270	0.019	0.418
Debt to Income ratio	0.416	0.002	0.786	0.354
Product of Debt and Inequality	-0.396	-0.765	0.007	0.354
Educational attainment high school	0.016	-0.143	0.172	0.407
Educational attainment college	-0.167	-0.337	0.015	0.392
Employment to population ratio	0.155	0.012	0.296	0.447
Export intensity – Sub-saharan Africa	-0.135	-0.379	0.079	0.337
Export intensity- South America	-0.057	-0.260	0.157	0.376
Export intensity- Oceania	0.200	0.037	0.379	0.407
Export intensity- North America	0.009	-0.185	0.193	0.393
Export intensity- Middle East	-0.747	-1.017	-0.501	0.361
Export intensity- North Africa	0.456	0.213	0.697	0.366
Export intensity- Europe	0.113	-0.077	0.304	0.393
Export Intensity- Asia	0.115	-0.079	0.298	0.361
Model posterior predictive SSE	2518.05			
R squared	0.374			

Table 8 reports the DPHLM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the Gini coefficient. In this case, the Gini coefficient has a negative coefficient on per-capita GDP growth, but this coefficient is not significant at the 75% posterior interval. Debt to GDP ratio has a positive and significant effect on per-capita GDP growth possibly suggesting

the hypothesis of debt led economic growth. The estimated Z-score coefficient varies between 0.002 and 0.78 for the first and third quartiles of the distribution. The product of debt and Gini coefficient is negative, but is not significant. The manufacturing export intensity of Oceania and North Africa are positive and significant suggesting higher spillovers from export earnings from these markets. However, the manufacturing export intensity from Middle Eastern markets is negative and significant, suggesting that net export earnings have negative effect on per-capita GDP growth from serving this particular market.

4.2. Normal Random Effect Model (NREM- Two level)

Bayesian estimation theory for the normal random effect model was introduced by Gilks et al. (1993). This model is given in equation system (11).

$$
\begin{aligned}
& y_{i(h)} \mid x_{i(h)} \sim f\left(y \mid x_{i(h)}\right),\ i(h) = 1, \dots, n_h \\
& f\left(y \mid x_{i(h)}\right) = n(y \mid x_{i(h)}\beta_{Rh}, \sigma^2) \\
& x.\beta_{Rh} = x.\beta + x.u_h \\
& \beta_0 \mid \sigma^2 \sim N(0, \sigma^2 v_{\beta 0} \to \infty) \\
& \beta_k \mid \sigma^2 \sim N\left(0, \sigma^2 v_\beta\right), \qquad k = 1, \dots, p \\
& u_h \mid T \sim N(0, T),\ \ h = 1, \dots, N_h \\
& \sigma^2 \sim IG\left({}^{a_0}/_{2}, {}^{a_0}/_{2}\right) \\
& T \sim IW(p+3,\ s_0 I_{p+1}
\end{aligned} \tag{11}
$$

In equation system (11), the index h indicates a group (at level 2), n_h is the number of observations in group h, and N_h denotes the total number of groups. The values of the prior parameters are as follows: $v_\beta = 1000; a_0 = 0.001;$ and $s_0 = 10$.Table 9 reports the NREM estimates for the median, first quartile, and the third quartile of the parameters of the model.

Table 9 reports the NREM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the income share of the top 1 percent. In this case, the income share of the top 1 percent is negative and significant at the 75% posterior interval. The estimated Z-score coefficient varies between -0.18 and -0.04 between the first and the third quartile of the distribution. Debt to GDP ratio also has a negative and significant effect on per-capita GDP growth. The estimated Z-score coefficient varies between -0.33 and -0.07 between the first and the third quartile of the distribution. The product of debt to GDP ratio and the income share of the top 1 percent coefficient are positive and significant at the 75% posterior interval excluding zero. The educational attainment at college coefficient turns out to be negative and significant at the 75% posterior interval, while the employment to population ratio coefficient is positive and significant. The manufacturing export intensity of Europe,

Oceania, Asia, North Africa, and North America is positive and significant suggesting higher spillovers from export earnings from these markets. However, the manufacturing export intensity from Sub-Saharan Africa, South America and the Middle eastern region is negative and significant, suggesting that net export earnings have negative effect on per-capita GDP growth from serving these particular markets. Overall, this model fits best to the data and is thus our preferred specification in terms of the Bayesian priors assumed.

Table 9: NREM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Income Share of the Top 1 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.116	-0.309	0.076	0.416
Income share of top 1percent	-0.115	-0.296	0.062	0.412
Debt to Income ratio	-0.373	-0.620	-0.120	0.345
Product of Debt and Inequality	0.345	0.075	0.603	0.327
Educational attainment high school	0.005	-0.172	0.183	0.419
Educational attainment college	-0.086	-0.274	0.100	0.410
Employment to population ratio	0.175	0.000	0.348	0.424
Export intensity – Sub-saharan Africa	-0.186	-0.389	0.014	0.402
Export intensity- South America	-0.034	-0.232	0.171	0.399
Export intensity- Oceania	0.030	-0.165	0.224	0.404
Export intensity- North America	0.289	0.095	0.483	0.414
Export intensity- Middle East	-0.418	-0.632	-0.195	0.380
Export intensity- North Africa	0.058	-0.161	0.299	0.361
Export intensity- Europe	0.315	0.131	0.497	0.424
Export Intensity- Asia	0.150	-0.045	0.343	0.415
Model posterior predictive SSE	2233.16			
R squared	0.387			

The conditional distribution of the Income share of the top 1 percent holding debt to GDP ratio constant has a negative effect on per-capita GDP growth across all quartiles.

Similarly, the conditional distribution of the debt to GDP ratio on per-capita GDP growth has a negative effect holding the income share of the top 1 percent constant.[7]

Table 10: NREM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Gini coefficient) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	-0.048	-0.224	0.126	0.435
Income share of top 10percent	-0.253	-0.421	-0.088	0.432
Debt to Income ratio	-1.182	-1.461	-0.933	0.318
Product of Debt and Inequality	1.205	0.946	1.485	0.311
Educational attainment high school	0.010	-0.169	0.191	0.404
Educational attainment college	0.000	-0.185	0.183	0.413
Employment to population ratio	0.109	-0.055	0.281	0.432
Export intensity – Sub-saharan Africa	-0.011	-0.218	0.193	0.387
Export intensity- South America	-0.320	-0.519	-0.099	0.371
Export intensity- Oceania	-0.043	-0.220	0.138	0.411
Export intensity- North America	0.225	0.032	0.417	0.425
Export intensity- Middle East	-0.176	-0.417	0.064	0.382
Export intensity- North Africa	0.127	-0.067	0.317	0.430
Export intensity- Europe	0.259	0.064	0.451	0.397
Export Intensity- Asia	0.133	-0.048	0.307	0.429
Model posterior predictive SSE	2245.97			
R squared	0.321			

Table 10 reports the NREM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the Gini coefficient. In this case, the Gini coefficient is negative and significant at the 75% posterior interval. The estimated Z-score coefficient varies between -0.28 and -0.13 between the first and the third quartile of the distribution. Debt to GDP ratio also has a negative and significant effect on per-capita GDP growth. The estimated Z-score

[7] We do not report the income share of the top 10 percent and the Theil T statistic as variables in the NREM Model as most of the coefficients were not significant in these regressions. These results can be obtained from the authors upon request.

coefficient varies between -1.03 and -0.29 between the first and the third quartile of the distribution. The product of debt to GDP ratio and the Gini coefficient are positive and significant at the 75% posterior interval excluding zero. None of the educational attainment measures attain significant, and the employment to population ratio coefficient is also not significant. The manufacturing export intensity of Europe, Oceania, Asia, North Africa, and North America is positive and significant suggesting higher spillovers from export earnings from these markets. However, the manufacturing export intensity from Sub-Saharan Africa, and the Middle eastern region is negative and significant, suggesting that net export earnings have negative effect on per-capita GDP growth from serving these particular markets.

The conditional distribution of the Gini coefficient holding debt to GDP ratio constant has a negative effect on per-capita GDP growth across all quartiles. Similarly, the conditional distribution of the debt to GDP ratio on per-capita GDP growth has a negative effect holding the income share of the top 1 percent constant.

4.3. Beta Process Mixture of Linear Regression Model (BPLM): Robustness of Estimates

We extend our regression models using the Beta process mixture of linear regression for robustness tests. The two parameter beta process was introduced by Ishwaran and Zarepour (2000). This model has additional covariates, such as an interaction term of dummy for recession with each regions of the U.S. The regions are classified as: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and far west.

A multivariate regression version of this model, and the associated MCMC estimation method of the model's posterior distribution were introduced by Karabatsos and Walker (2012b) and is given as follows:

$$
\begin{aligned}
&\left(y_{i(h)}\right)_{i(h)=1}^{n_h} | X_h \sim f(\, y_h \mid X_h\,),\ h = 1, \dots\dots, N_h \\
&f(\, y_h \mid X_h\,) = \sum_{j=1}^{\infty} \left\{ \prod_{i(h)=1}^{n_h} n(y_{i(h)} \mid\ x_{i(h)}\beta, {\sigma_j}^2) \right\} \omega_j \\
&\omega_j = v_j \prod_{l=1}^{j-1} (1 - v_l) \\
&v_j \sim Be(a, b) \\
&\beta_j \mid \mu, T \sim N(\mu, T) \\
&{\sigma_j}^2 \sim IG({}^{a_0}/_{2}, {}^{a_0}/_{2}) \\
&\mu, T \sim N\left(\mu \mid 0, r_0 I_{p+1}\right) IW(T \mid p+3, s_0 I_{p+1})
\end{aligned}
\tag{12}
$$

In equation system (12), the index h indicates a group (at level 2), n_h is the number of observations in group h, and N_h denotes the total number of groups. The prior parameters assumed in the model are as follows: $a = 1$; $b = 1$; $r_0 = 10$; $s_0 = 10$; and $a_0 = 5$.

Table 11: BPLM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Income Share of Top 1 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.012	-0.101	0.125	0.474
Income share of top 1 percent	-0.107	-0.227	0.008	0.441
Debt to Income ratio	-0.351	-0.519	-0.209	0.343
Product of Debt and Inequality	0.302	0.159	0.480	0.332
Educational attainment high school	0.026	-0.084	0.136	0.470
Educational attainment college	-0.050	-0.164	0.063	0.459
Employment to population ratio	-0.027	-0.136	0.084	0.468
Export intensity – Sub-saharan Africa	-0.206	-0.325	-0.086	0.436
Export intensity- South America	-0.154	-0.276	-0.031	0.436
Export intensity- Oceania	0.160	0.047	0.276	0.458
Export intensity- North America	0.165	0.045	0.287	0.451
Export intensity- Middle East	-0.180	-0.305	-0.056	0.428
Export intensity- North Africa	0.122	-0.016	0.259	0.408
Export intensity- Europe	0.274	0.156	0.390	0.459
Export Intensity- Asia	0.114	0.002	0.227	0.463
Model posterior predictive SSE	1496.09			
R squared	0.499			

Table 11 reports the BPLM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the income share of the top 1 percent in the income distribution. In this case, the coefficient of the income share of the top 1 percent is negative but not significant at the 75% posterior interval. The estimated Z-score coefficient varies between -0.23 and -0.008 between the first and the third quartile of the distribution. Debt to GDP ratio also has a negative and significant effect on per-capita GDP growth. The estimated Z-score coefficient varies between -0.52 and -0.21 between the first and the third quartile of the distribution. The product of debt to GDP ratio and the income share of the top 1 percent are positive and significant at the 75%

posterior interval excluding zero. None of the educational attainment measures attain significance, and the employment to population ratio coefficient is also not significant. The manufacturing export intensity of Europe, Oceania, Asia, and North America is positive and significant suggesting higher spillovers from export earnings from these markets. However, the manufacturing export intensity from Sub-Saharan Africa, South America, and the Middle eastern region is negative and significant, suggesting that net export earnings have negative effect on per-capita GDP growth from serving these particular markets. We also included the dummy for recession and interacted this variable with each 8 regions for the U.S. We find that this interaction term is negative for each region, suggesting that recessions have negative effect on economic growth during a downturn. This is consistent with findings from other studies in the literature (Stiglitz, 2015; Gordon, 2012).

The conditional distribution of the income share of the top 1 percent holding debt to GDP ratio constant has a negative effect on per-capita GDP growth in the first two quartiles. However, the conditional distribution of the income share of the top 1 percent has a positive effect on per-capita GDP growth rate on the third quartile, suggesting higher income inequality may have positive effects on economic growth at higher quartiles of the income distribution. Similarly, the conditional distribution of the debt to GDP ratio on per-capita GDP growth has a negative effect holding the income share of the top 1 percent constant.

Table 12 reports the BPLM estimates for the median, first quartile, and the third quartile of the parameters of the model. The measure of inequality considered is the income share of the top 10 percent in the income distribution. In this case, the coefficient of the income share of the top 10 percent is negative and significant at the 75% posterior interval. The estimated Z-score coefficient varies between -0.23 and -0.018 between the first and the third quartile of the distribution. Debt to GDP ratio also has a negative and significant effect on per-capita GDP growth. The estimated Z-score coefficient varies between -1.23 and -0.96 between the first and the third quartile of the distribution. The product of debt to GDP ratio and the income share of the top 1 percent are positive and significant at the 75% posterior interval excluding zero. None of the educational attainment measures attain significance, and the employment to population ratio coefficient is also not significant. All the dummy recession variable interacted with each region has a negative coefficient and is significant, suggesting that recessions have a negative effect on per-capita GDP growth.

The manufacturing export intensity of Europe, Asia, and North America is positive and significant suggesting higher spillovers from export earnings from these markets. However, the manufacturing export intensity from Sub-Saharan Africa, and the Middle

eastern region is negative and significant, suggesting that net export earnings have negative effect on per-capita GDP growth from serving these particular markets.

Table 12: BPLM Posterior Estimates of Public Debt to GDP Ratio and Income Inequality (Income Share of Top 10 percent) on Per-Capita GDP Growth Rate

Variables	Median Estimate	1st Quartile Estimate	3rd Quartile Estimate	CUSUM
C	0.087	-0.027	0.200	0.471
Gini Coefficient	-0.124	-0.232	-0.018	0.473
Debt to Income ratio	-1.094	-1.228	-0.963	0.401
Product of Debt and Inequality	1.127	0.998	1.255	0.400
Educational attainment high school	0.023	-0.084	0.132	0.470
Educational attainment college	-0.063	-0.174	0.048	0.466
Employment to population ratio	-0.015	-0.124	0.093	0.471
Export intensity – Sub-Saharan Africa	-0.261	-0.377	-0.144	0.446
Export intensity- South America	-0.110	-0.231	0.010	0.438
Export intensity- Oceania	0.117	-0.005	0.238	0.425
Export intensity- North America	0.372	0.251	0.495	0.433
Export intensity- Middle East	-0.238	-0.380	-0.099	0.371
Export intensity- North Africa	0.093	-0.041	0.235	0.395
Export intensity- Europe	0.439	0.309	0.568	0.404
Export Intensity- Asia	0.204	0.088	0.321	0.444
Model posterior predictive SSE	1535.64			
R squared	0.490			

The conditional distribution of the income share of the top 10 percent holding debt to GDP ratio constant has a negative effect on per-capita GDP growth in all the quartiles. Similarly, the conditional distribution of the debt to GDP ratio on per-capita GDP growth has a negative effect holding the income share of the top 10 percent constant.[8]

[8] We do not report the BPLM results for the Gini coefficient and the Theil T statistic, as the main coefficients, such as to debt to GDP ratio and measures of inequality were not significant. These results can be obtained from the authors upon request.

6. Conclusions and Policy Implications

We presented a Bayesian regression model to understand the interactions of debt, income inequality and economic growth for U.S. states over the period 1987-2011. This particular period is chosen as both income inequality and public debt started increasing for most U.S. states. We highlight the main results, give conclusion and policy implications. First, income inequality is lowering per-capita GDP growth for most states, owing to lower social mobility and lower tax revenues. This is adversely impacting the economic growth rate of states, especially after the financial crisis of 2007-08.

Second, the coefficient of the product of public debt to GDP ratio and income inequality measure has positive effect on per-capita GDP growth rate. This may suggest that higher public expenditures in the short-run in infrastructure and R&D investments on the part of the federal government are desirable.

Third, educational attainment of college graduates is often having a negative effect on per-capita GDP growth rate. This may suggest that there is room for state governments to improve public education by investing in charter schools and employing quality teachers to reverse this situation.

Fourth, the coefficient of debt to income ratio has ambiguous effect on per-capita GDP growth rates. Depending on the Bayesian priors chosen, we have either positive or negative effects on economic growth. This may suggest two things: (a) Debt to income ratio is already quite high and is having a negative effect on economic growth; and (b) Debt to income ratio is high, but public investments such as grants to states in the forms of infrastructure and R&D investments can improve economic growth in the long-run. Further research is clearly needed in this subject.

Fifth, we find the manufacturing export intensity is unambiguously positive for exports to North America, Europe and Asia, suggesting higher spillovers and export revenues from these markets. On the other hand, manufacturing export intensity is unambiguously negative for Sub-Saharan Africa, and the Middle Eastern region, implying negative export revenues from these markets. This result may suggest that there is considerable scope for diversifying into different markets for states in order to improve their economic growth.

Sixth, the conditional distribution of Theil T-statistic holding debt to GDP ratio constant has a positive effect on per-capita GDP growth across all quartiles. Similarly, the conditional distribution of debt to GDP ratio on per-capita GDP growth rate has a positive effect holding the Theil T-statistic constant. These results may suggest that debt augmenting growth may take place if inequality measure can be decomposed into within and between group components.

The main innovation of our study is two-fold. First, we conduct a least squares baseline Bayesian regression model to test our initial findings. As the model fit was not good, we use different Bayesian priors, such as DPHLM, PYLM, NREM, and NIGLR priors to test our baseline model. Later, we validate our model using the Beta process priors of the linear regression model. The main conclusions of our study are validated using the latter test.

Our results have few implications for state governments and the federal governments' revenues and expenditure patterns. First, our results suggest that there is room in the short-run for the federal government to increase spending on infrastructure and R&D investments by injecting more money to the states. This is given by the positive coefficient of the debt and income inequality term in the various Bayesian models. Although, this will increase public debt in the short-run and in the long-run, higher tax revenues from these investments will generate more jobs and thus improve the fiscal sustainability of states.

Second, our results imply that income inequality has significantly increased during the past three decades. Along with the rise in income inequality, the fiscal situation of states is also precarious, such as the recent public debt crisis for the state of Connecticut. These trends need to be reversed by investing in technological innovations and in high school and college education. Our high school students perform significantly lower than students from other developed nations, such as Finland and South Korea in reading comprehension and mathematics. A better quality education can be accomplished by eliminating teacher unions at the state levels, and through recruiting and retention of the best teachers in schools and colleges by proper incentives.

References

Afonso, A., and J.T. Jalles, 2013, Fiscal Composition and Long-Term Growth, European Central Bank Working Paper No. 1518.

Alesina, A., and D. Rodrik, 1994, Distributive Politics and Economic Growth, Quarterly Journal of Economics, 109(2), 465-490.

Barro, R.J., 2000, Inequality and growth in a panel of countries, Journal of Economic Growth, 5, 5-32.

Bond, S., 2002, Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice, cemmap Working Paper No. CWP09/02.

Brooks, S., 1998, Markov chain Monte Carlo method and its application, Journal of the Royal Statistical Society: Series D (The Statistician), 47, 69-100.

Castells-Quintina, D., and V. Royuela, 2012, Unemployment and long-run economic growth: The role of income inequality and urbanization, Investigaciones Regionales, 24, 153-173.

Checherita, C., and P. Rother, 2010, The Impact of high and growing government debt on economic growth – an empirical investigation for the euro area, ECB Working Paper No. 1237.

Cooper, M., and M.W. Walsh, 2010, Crushing Debt Facing State Governments Stokes Fear in Financial Analysts, The Boston Globe, December 5, 2010.

Cowell, F.A., 1995, Measuring Inequality (2nd edition), Harvester Wheatsheaf, Hemel Hempstead.

Davtyan, K., 2014, Interrelation among Economic Growth, Income Inequality, and Fiscal Performance: Evidence from Anglo-Saxon Countries, University of Barcelona Working Paper No. 2014/05.

de Dominicis, L., R.J. Florax, and H.L. De Groot, 2008, A meta-analysis on the relationship between income inequality and economic growth, Scottish Journal of Political Economy, 55(5), 654-682.

Durlauf, S.N., P. Johnson, and J. Temple, 2005, Growth Econometrics, In Handbook of Economic Growth, P. Aghion and N. Durlauf, eds., North Holland, Amsterdam.

Favaro, S., A. Lijoi, and I Prunster, 2012, On the Stick-Breaking Representation of Normalized Inverse Gaussian Priors, Biometrika, 99, 663-674.

Ferguson, T. (1973), A Bayesian Analysis of Some Nonparametric Problems, Annals of Statistics, 1, 209-230.

Frank, M.W., 2009, Inequality and Growth in the United States: Evidence from a New State-Level Panel of Income Inequality Measures, Economic Inquiry, 47(1), 55-68.

Frank, M.W., 2014, A New State-Level Panel of Annual Inequality Measures over the Period 1916-2005, Journal of Business Strategies, 31(1), 241-262.

Friedman, J., 2001, Greedy function approximation: A gradient boosting machine, Annals of Statistics, 29, 1189-1232.

Galor, O., and O. Moav, 2004, From Physical to Human Capital Accumulation: Inequality and the Process of Development, Review of Economic Studies, 71, 1001-1026.

Gelfand, A., and J. Ghosh, 1998, Model choice: A minimum posterior predictive loss approach, Biometrika, 85, 1-11.

Gilks, W., C. Wang, B. Yvonnet, and P. Coursaget, 1993, Random-Effects Models for Longitudinal Data Using Gibbs Sampling, Biometrics, 49, 441-453.

Gordon, R.J., 2012, Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds, NBER Working Paper No. 18315.

Gordon, R.J., 2014, The Demise of U.S. Economic Growth: Restatement, Rebuttal, and Reflections, NBER Working Paper No. 19895.

Karabatsos, G., and S. Walker, 2012b, Bayesian Nonparametric Mixed Random Utility Models, Computational Statistics and Data Analysis, 56, 1714-1722.

Karabatsos, G., 2015, Bayesian Nonparametric Regression for Educational Research, 2015 Annual Meeting Professional Development Course, Swissotel, Event Center Second Level, Vevey 1 & 2.

Kourtellos, A., and C.G. Tsangarides, 2015, Robust Correlates of Growth Spells: Do Inequality and Redistribution Matter? The Rimini Center for Economic Analysis Working Paper No. 15-20.

Kumar, M.S., and J. Woo, 2010, Public Debt and Growth, IMF Working Paper No. WP/10/174.

Larch, M., 2012, Fiscal Performance and Income Inequality: Are Unequal Societies More Deficit-Prone? Kyklos, 65(1), 53-80.

Lijoi, A., R. Mena, and I. Prunster, 2005, Hierarchical Mixture Modeling with Normalized Inverse-Gaussian Priors, Journal of the American Statistical Association, 100, 1278-1291.

Lindley, D., and A. Smith, 1972, Bayes Estimates for the Linear Model, Journal of the Royal Statistical Society, 34(1), 1-41.

Milanovic, B., 1999, Do more unequal countries redistribute more? Does the median voter hypothesis hold? World Bank Policy Research Working Paper No. 2264, Washington, DC.

Minea, A., and A. Parent, 2012, Is High Public Debt Always Harmful to Economic Growth? Reinhart and Rogoff and some Complex Non-linearities, CERDI Working Paper No. 2012-18.

Nishi, H., 2012, Varieties of Economic Growth Regimes, Types of Macroeconomic Policies, and Policy Regimes: A Post-Keynesian Analysis, Kyoto University Working Paper No. E-12-008.

Panizza, U., and A.E. Presbitero, 2013, Public Debt and Economic Growth in Advanced Economies: A Survey, Graduate Institute of Geneva Working Paper No. 78.

Persson, T., and G. Tabellini, 1994, Is Inequality Harmful for Growth? American Economic Review, 84(3), 600-621.

Pesaran, M., and R. Smith, 1995, Estimating long-run relationships from dynamic heterogeneous panels, Journal of Econometrics, 68(1), 79-113.

Pesaran, M.H., Y. Shin, and R.P. Smith, 1999, Pooled mean group estimation of dynamic heterogeneous panels, Journal of the American Statistical Association, 94, 621-634.

Pitman, J., and M. Yor, 1997, The Two-Parameter Poisson-Dirichlet Distribution Derived from a Stable Subordinator, Annals of Probability, 25, 855-900.

Reinhart, C.M., and K.S. Rogoff, 2010a, Growth in a Time of Debt, American Economic Review, Papers & Proceedings, 100.

Reinhart, C.M., and K.S. Rogoff, 2010a, Growth in a Time of Debt, NBER Working Paper No. 15639.

Reinhart, C.M., V.R. Reinhart, and K.S. Rogoff, 2012, Debt Overhangs: Past and Present, NBER Working Paper No. 18015.

Robert, C.P., and G. Casella, 2010, Introducing Monte Carlo Methods with R, Springer.

State Budget Crisis Task Force, 2012, Report of the State Budget Crisis Task Force.

Stiglitz, J.E., 2015, The Great Divide: Unequal Societies and What we can do about Them? W.W. Norton and Company, New York.

Zhao, B., and D. Coyne, 2013, Walking a Tightrope: Are U.S. State and Local Governments on a Fiscally Sustainable Path? Boston Fed Working Paper No. 13-18.

Appendix A: PYHLM and NIGLR Models

A.1: PY Process Mixture of Homoscedastic Linear Regression Model Priors (PYHLM)

Following Ferguson (1973), Pitman & Yor (1997) and Karabatsos and Walker (2012b), a multivariate regression model, and the associated MCMC estimation method of the model's posterior distribution is given as follows:

$$
\begin{aligned}
&(y_{i(h)})_{i(h)=1}^{n_h} | X_h \sim f(\, y_h \mid X_h\,),\ \ h = 1, \dots \dots, N_h \\
&f(\, y_h \mid X_h\,) = \sum_{j=1}^{\infty} \left\{ \prod_{i(h)=1}^{n_h} n(y_{i(h)} \mid x_{i(h)}\beta_j, \sigma^2) \right\} \omega_j \\
&\omega_j = v_j \prod_{l=1}^{j-1} (1 - v_l) \\
&v_j \sim Be(1 - a, b + aj) \\
&\beta_j \mid \mu, T \sim N(\mu, T) \\
&\sigma^2 \sim IG({}^{a_0}/_{2}, {}^{a_0}/_{2}) \\
&\mu, T \sim N\big(\mu \mid 0, r_0 I_{p+1}\big) IW(T \mid p + 3, s_0 I_{p+1})
\end{aligned}
\tag{A.1}
$$

Equation system (A.1) is known as the Pitman-Yor process. When $0 \leq a \leq 1$ and $= 0$, it is equivalent to the normalized stable process; when $a = 0$, this is equivalent to the Dirichlet process (Ferguson, 1973), with precision parameter $b > 0$. In the above equation system, *h* indicates a group (at level 2), n_h is the number of observations in group *h,* and N_h denotes the total number of groups. The following values of priors are assumed: $a = 0.5$; $b = 1$; $r_0 = 10$; $s_0 = 10$; and $a_0 = 5$.

The results of this model are qualitatively similar to the DPHLM model, and these results can be obtained from the authors upon request.

A.2: NIG Process Mixture of Linear Regression Model (NIGLR)

In this model, the mixture distribution is assigned a normalized inverse-Gaussian $NIG(c, G_0)$ process prior distribution with precision parameter $c > 0$ and baseline distribution $G_0 = N(\mu, T)$ (Lijoi et al., 2005). A stick-breaking representation of the $NIG(c, G_0)$ process is used (Favaro et al., 2012). For estimating the posterior distribution of this model, the software implements the MCMC methods from Karabatsos and Walker

(2012b). In equation system (5), the index h indicates a group (at level 2), n_h is the number of observations in group h, and N_h denotes the total number of groups.

$$\left(y_{i(h)}\right)_{i(h)=1}^{n_h} | X_h \sim f(\, y_h \mid X_h\,),\ \ h = 1, \dots \dots, N_h$$

$$f(\, y_h \mid X_h\,) = \sum_{j=1}^{\infty} \left\{ \prod_{i(h)=1}^{n_h} n(y_{i(h)} \mid\ x_{i(h)}\beta, {\sigma_j}^2) \right\} \omega_j$$

$$\omega_j = v_j \prod_{l=1}^{j-1} (1 - v_l)$$

$$v_j \sim {v_{1j}}\Big/{\left(v_{1j} + v_{0j}\right)}$$

$$v_{ij} \sim GIG\left({c^2}\Big/{\textstyle\prod_{l=1}^{j-1}}\left(1 - v_j\right), 1 - \tfrac{j}{2}\right)$$

$$v_{oj} \sim IG\left({}^{1}\!/_{2}, 2\right)$$

$$\beta_j \mid \mu, T \sim N(\mu, T)$$

$${\sigma_j}^2 \sim IG\left({}^{a_0}\!/_{2}, {}^{a_0}\!/_{2}\right)$$

$$\mu, T \sim N\left(\mu \mid 0, r_0 I_{p+1}\right) IW\left(T \mid p + 3, s_0 I_{p+1}\right) \qquad \text{(A.2)}$$

The following values of the priors are assumed: $c = 1$; $r_0 = 10$; $s_0 = 10$; and $a_0 = 5$. Our results from the DPHLM estimates also hold for the NIGLR model. These results can be obtained from the authors upon request.