Chapter

The Nonlinear Dynamic Impact of Development-Inequality in the Prudential Policy Regime in Emerging Economies: A Bayesian Spatial Lag Panel Smooth Transition Regression Approach

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Abstract

A panel data analysis of the nonlinear dynamics of economic-development in a macroprudential policy regime was conducted in a panel of 25 emerging markets who were grouped together based on their regions: 10 African countries, 8 Asian countries, and 7 European countries covering the period 2000–2019. The paper explored the validity of the Kuznets hypothesis in a prudential policy regime as well as the threshold level at which economic-development reduces inequality, using the Bayesian Spatial Lag Panel Smooth Transition Regression model. This model was adopted due to its ability to address the problems of endogeneity, heterogeneity, and time and spatial-varying in a nonlinear framework. We found evidence of a nonlinear effect between the two variables, where the threshold was found to be US $15,900, above which reduces inequality in the African emerging markets; while for emerging Asian and emerging European markets, we documented a U-shape relationship with an optimal level of economic-development estimated at US$17,078 and US$19,000, respectively. Unconventional and macroprudential policies were found to trigger development-inequality relationships. The result supported the S-curve relationship in these regions. Our evidence largely suggests that policymakers ought to formulate policies aiming at increasing agricultural productivity through land redistribution, investment, trade, and promoting human development. Policymakers should also be cautious when implementing macroprudential and unconventional monetary policies.

Keywords: economic-development, emerging markets, income inequality, BPSTR model, macroprudential policies

1. Introduction

The effect of economic development on income inequality has been a debated subject for the past decades. To date, there have been controversies in both the theoretical predictions and empirical literature on identifying the role played by economic development in income inequality. Theories, such as the Kuznets hypothesis, postulate that there is nonlinearity between economic development and income inequality, stating that inequality tends to escalate during the early phase of development, as labour migrates from the low-paying sector, agriculture, to the high-paying sector, urban and non-agricultural economic activities [1]. The Kaldor theory states that, if capitalists save more than workers, fast rates of growth are associated with a higher share of the profits [2]. After 41 years of the Kuznets hypothesis, Tribble [3], became famous as the Tribble S-shape hypothesis. Tribble [3] posits that the Kuznets inverted U-shape was not premised on the data relating to the agricultural to manufacturing (ATM) structural transition, as the study by Kuznets mentions the first critical turning point, where the economic integration of the modern sector of manufacturing with the traditional sector had started in earnest. The extant literature on the development-inequality relationship is vast and has capitulated extensive conflicting outcomes. The contradiction that emerged in the literature is mostly due to, but not limited to, different model specifications, data sets and estimation techniques, or the levels of the economies being studied when examining the development-inequality relationship. For instance, studies that believe in nonlinearity contradict each other, as portrayed by those who support the existence of the Kuznets inverted U-shape [4–9] or no U-shape [5, 10, 11], or the S-shape [12, 13]. There are also studies that find this relationship to be inconclusive [14, 15] or a mixed relationship [12].

The current study seeks to extend the existing literature on this subject matter, following the seminal work of Zungu et al. [9], whose study adopted the PSTR in a panel of 15 emerging economies. Their study tested the existence of the Kuznets hypothesis during the prudential and non-prudential policy regimes in emerging economies. To capture economic development, their study used GDP per capita at constant prices (US$), while income inequality was captured by the Gini coefficient at market price. Their study controlled for house prices, government expenditure, investments and macroprudential policy, using capital-related and borrower-related instruments. The current work aims to extend the study documented by Zungu et al. [9], As it is argued in their study and others, those monetary policies, especially the macroprudential policies, may have a direct or indirect impact on income inequality. However, in their study, they focus mainly on two macroprudential policy instruments, namely the capital and borrower-related instruments, conversely neglecting the potential impact of other macroprudential policy measures in the system such as FX and/or countercyclical reserve requirements, and a general countercyclical capital buffer/requirement.

We believe that it would be quite interesting to control for other policy instruments that were not captured in their study, as they might play a significant role in triggering the development-inequality correlation when these countries switch from the era of a non-prudential policy regime to a prudential policy regime. As it has been noted in the literature, the estimation techniques or the level of the economy being studied when examining the development-inequality relationship also triggered the documented results in this subject matter. Moreover, in the estimation techniques, studies on this subject, especially those that have investigated this problem in a panel-data framework, have introduced time and cross-sectional effects to represent individual heterogeneity, which then satisfies the assumption that the coefficients of the explanatory variables are assumed to be constant for all section units and periods. However, in practice, this assumption is sometimes unreasonable. For example, the model adopted by Zungu et al. [9] actually allows coefficients to change with different cross sections and times, which is a sufficient relaxation of the heterogeneity assumption in panel-data models. Let us consider a scenario where the local equilibrium prices of all local markets are correlated in the general equilibrium model; individuals in the network model are interconnected; and in a competitive market, one participant's decision is influenced by the decisions of other participants, and so on. The classic econometric model would no longer be applicable when dealing with the aforementioned study areas. The spatial method plays a significant role in such a problem instead.

To address these issues, we separated countries based on their regions and continued to focused on those that are emerging countries from Africa (Burkina Faso, Ghana, Mali, Botswana, Namibia, South Africa, Tanzania, Mozambique, Uganda, and Eswatini), emerging Asian economies (China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand), and emerging European economies (Czech Republic, Hungary, Poland, Romania, Russia, Turkey, and the Ukraine). The primary objective behind categorizing these countries by their respective regions is to compare and track if the correlation between the variables of interest is substantially impacted by the country's location. Therefore, we establish a model for the emerging markets by extending the PSTR model developed by González et al. [16] to account for spatial correlation between variables, and we also construct a Bayesian inference for the PSTR model. The Bayesian method has the advantage of completely utilizing priori and posteriori information, resulting in improved estimation accuracy and resilience. Considering the model, the group of countries being studied and the variable adopted in the model, we believe that this will provide new insights into the emerging literature.

The main advantage of the standard PSTR model is that it can handle time heterogeneity and cross-sectional data. This approach, however, cannot handle spatial data with cross-sectional correlation. To combine the benefits of the spatial model with the PSTR model, we incorporate spatial correlation into the PSTR model and develop a spatial lag panel smooth transition regression (SLPSTR) model that can adequately account for heterogeneity and spatial correlation simultaneously. We then propose a Bayesian inference method for our model, in contrast to the frequentist estimation methods widely used in the econometric literature, such as the Generalized Moment Method (GMM), the (Quasi) Maximum Likelihood Method, the Instrumental Variable (IV) Method for estimating spatial econometric models, and the Nonlinear Least Squares Method for estimating PSTR models. The utilization of information is the most essential element of a Bayesian estimate when compared to the frequentist approach. The Bayesian method determines both sample and prior information, whereas the frequentist method just considers sample information. We combined the Bayesian method with spatial correlation, following Li et al. [17]. The linear model has been used in the current literature on the spatial model, with the assumption that the influence of the independent variables on the dependent variable is linear and the marginal effects are constant throughout space and time. However, our paper differs from the above assumption in that we introduce a nonlinear influence form of "regime transition" into the spatial econometric model and obtain the Bayesian spatial panel smooth transition model, which allows the influence of independent variables on the dependent variable to change with some transition variables Li et al. [17]. Our argument is that, because the transition variable often varies across time and space, the effect of the independent variables can also be time and spatial-varying, which weakens the linear model's assumption that the coefficients of independent variables are constant.

The remaining portion of the paper is organized as follows. Section 2 briefly surveys the related literature. Section 3 presents an overview of the model. Section 4 discusses the results of the SLPSTR models. Section 5 provides concluding remarks and discusses policy implications.

2. Literature review

2.1 Theoretical debate on economic development and income inequality

There is a theoretical controversy in the literature on the development-inequality relationship. The following section briefly discusses both the Kuznets and the Tribble hypotheses. According to the Kuznets theory, Kuznets [1], development-inequality is characterized by two regimes with one threshold of development, where in the early stage of development, income inequality increases as labor migrates from the low-paying sector, agriculture, to the high-paying sector, urban and non-agricultural economic activities. Kuznets [1] made the following assumption and formulated the following function:

$$GINI = \beta_0 + \beta_1 ECD - \beta_2 ECD^2 + \mu, \tag{1}$$

The Kuznets theory highlights two phases of the economy, with the first represented by the coefficient $\beta_1 ECD$ (economic development), which emphasizes that, during the first stage, industrial growth creates inequality as the weight of the non-agricultural sector expands. The second phase of the economy, develops when the agricultural sector's proportion of the labor diminishes, a threshold is achieved, and inequality begins to reduce (due to the agricultural and rural sectors' very low weight), as evidenced by the coefficient $\beta_2 ECD^2$ (economic development). Following Kuznets' theory, we utilized GDP per capita as a proxy for economic progress in our analysis.

After the intervention suggested by Kuznets [1] in this subject matter, fourth 1 years later, Tribble [3] tested the validity of Kuznets's hypothesis, and found that the Kuznets inverted U-shape was not premised on the data relating to an agricultural to manufacturing (ATM) structural transition, as the study based on the Kuznets hypothesis mentions the first critical turning point, where the economic integration of the modern sector of manufacturing with the traditional sector had initiated in earnest. This might be due to the fact that the data employed by Simon Kuznets did not aptly define the structural shift in sectoral development, but merely presumed that the shift had been made.

However, the recent data embrace not only the period beyond the first critical turning point, which Kuznets predicted correctly, but also the second critical turning point related to the manufacturing to services (MTS) transition, which may not have been anticipated as a structural shift in economic development. Therefore, Tribble [3] defined a shift that embraces numerous structural turning points in the development process, leading to the formulation of the S-curve which can be mathematically expressed as follows:

$$GINI = \beta_0 + \beta_1 PGNP - \beta_2 PGNP^2 + \beta_3 PGNP^3 + \mu, \beta_1 > 0, \beta_2 < 0, \beta_3 > 0, \quad |\beta_1| > |\beta_2| > |\beta_3| \tag{2}$$

Tribble [3] defines the model above as the phases that distinguish the S-curve as follows: Phase 1 (ATM) $\acute{f}(PGNP) > 0$ income-inequality and $\ddot{f}(PGNP) > 0$; increase at a cumulative rate. Phase 2 $\acute{f}(PGNP) > 0$ income-inequality and $\ddot{f}(PGNP) < 0$; increase at a decreasing rate. Therefore, the turning point is where $\acute{f}(PGNP) = 0$, and the first critical turning point has been archived at $\ddot{f}(PGNP) < 0$. Phase 3 $\acute{f}(PGNP) < 0$ income-inequality and $\ddot{f}(PGNP) > 0$ increase at a cumulative rate. For Phase 4 $\acute{f}(PGNP) < 0$ income-inequality and $\ddot{f}(PGNP) > 0$ surge upwards at a decreasing rate. The turning point $\acute{f}(PGNP) = 0$, where the second critical turning point archived will be $\ddot{f}(PGNP) < 0$. For the MTS, phase 1 $\acute{f}(PGNP) > 0$, income-inequality $\ddot{f}(PGNP) > 0$ increases at a cumulative rate.

2.2 Empirical review

After scrutinizing the existing literature on this subject matter, we found that there are two strands of literature that explain the relationship between economic development and income inequality. The first strand is based on the seminal work document by Kuznets [1], of an inverted U-shape [4–9, 13, 18, 19], or no U-shape [5, 10, 11]. The second strand is based on the extension of the Kuznets curve, which is known as the S-shape, established by [3, 12, 13]. Apart from these two strands, there are studies that find the relationship in this subject matter to be inconclusive [14, 15], or a mixed relationship [12].

After reviewing the literature, we found one relevant paper on this subject matter by Zungu et al. [9], who introduced an adaptation of a macroprudential policy regime in their model. Their findings make a significant contribution to the literature and help to establish a connection between development and inequality in a macroprudential policy area. To control for macroprudential instrumental channels, their study adopted borrower-related and capital instruments. We believe that their study faced two constraints in producing a clear understanding of the developmental-inequality relationship in the macroprudential policy regime, as their study focused on a group of macroprudential instruments, ignoring the potential impact of the other macroprudential instruments. Their study further suffers from model weaknesses to account for spatial problems in variables.

Going as far back as Robinson [8], who tested, and indeed confirmed the Kuznets hypothesis, this contradicts with the finding documented by Ahluwalia [14], as the results show no support of the Kuznets hypothesis in a cross-country. The results documented by Robinson [8] were supported by the study conducted by Papanek and Kyn [18] using panel data of 83 countries over the period 1952–1978. In their model, income inequality was captured by the Gini coefficient, while economic development was captured by GDP per capita. The argument was taken forward by Jha [20] in a panel of 76 countries over the period 1966–1992, using pool regression. In their model the share of total income accruing to the poorest 20% of the population was adopted to capture income inequality, while per capita GDP was used to capture economic development while controlling for years of schooling and economic growth. They asserted that the data utilized for inequality caused a serious issue, potentially leading to an inaccurate result and/or nullifying the estimations which support the arguments made by Saith [21] in a case of 60 countries, that studies conducted in the 70s were found to be based on defective statistics and questionable methodological premises.

After 45 years of the argument on the nonlinear relationship between economic development and income inequality since the seminal work by Kuznets [1], the study by Barro [15] emerged with some strong criticism against the Kuznets hypothesis that it did not fully explain the impact of economic development on inequality over time. Barro's model includes controls for education, trade openness, the rule of law, and the democracy index. In the same year as Barro [15], a U-shape relationship was documented by Savvidesa and Stengos [11] in a panel of 95 countries. This contradicts the findings reported by Robinson [8], Ahluwalia [14], Papanek and Kyn [18], Jha [20]. The study by Savvidesa and Stengos [11] utilized the data from Deininger-Squire [22] to capture income inequality, with per capita income used as a proxy for economic development. On the other hand, the study by Shahbaz [12] supported the argument made by Barro [15]. The study by Shahbaz [12] was investigated in Pakistan using the ARDL bounds-testing approach on time-series data over the period 1971–2005. The development inequality in the case of Pakistan was found to be explained by the S-shape relation. This then further supported the Tribble hypothesis [3]. Although the study by [10] contradicts the findings reported by Robinson [8], Ahluwalia [14], Papanek and Kyn [18], Shahbaz, [12], and [8, 23] their study in a panel of 32 countries supports the results documented by Savvidesa and Stengos [11].

Following the seminal work documented by Tribble [3], which became popular as the Tribble S-shape hypothesis, the development-inequality relationship seems to change the paradigm, as studies that support the existence of the Tribble hypothesis emerge in the literature. Theyson and Heller [13] tested the Kuznets hypothesis in a panel of 147 countries from 1992 to 2007, utilizing a panel fixed-effect technique. Their finding supported the Tribble hypothesis. and were in line with the findings documented by Savvidesa and Stengos [11] and Angeles [10]. The U-shape relationship, which was first demonstrated by Savvidesa and Stengos [8], was further supported by the study documented by in a panel of 162 countries, covering the period 1960–2011. The study by Chiu and Lee [5], investigated the Kuznets hypothesis in a panel of 59 countries over the period 1985–2015, where these countries were classified into low-income (27) and high-income (32) countries. Their discovery made a significant contribution to the literature because it demonstrated that the Kuznets hypothesis holds true for low-income countries, while a U-shape explains the relationship in high-income countries. Kavya and Shijin [6] studied the impact of economic development on income inequality in a panel of 85 countries, where 16 were low-income, 28 were high-income and 41 were middle-income countries over the 1984–2014 period, using a GMM model. The findings reveal that the Kuznets curve holds for high-income countries.

Recently, Lee et al. [7] investigated the same subject matter in a panel of 68 countries from 2001 to 2018. Their findings supported the Kuznets hypothesis. Previous income inequality enhances current inequality in a regime with low economic development, while this effect is the opposite in a regime with high development. The argument was taken further by Zungu et al. [9], who investigated the development-inequality relationship in macroprudential and non-prudential policy regimes in a panel of 15 emerging markets covering the period 1985–2019. Their model accounts for borrower-related and capital-related instruments. Their finding documented two significant results for emerging markets, as they found a nonlinear relationship between the two variables, with the threshold being US $13,800, above which economic development reduces inequality. They further supported the argument that a macroprudential policy instrument increases inequality. Their study supported the empirical studies documented by Robinson [8], Ahluwalia [14], Papanek and Kyn [18], Jha [20], Kavya and Shijin [6], Lee et al. [7]. As the current study aims to introduce the impact of macroprudential policy regulations on development-inequality, this section explains the empirical relationship between a macroprudential policy and income inequality in a nutshell. The empirical research on the distributional impact of macroprudential policies indicates that the increased adoption of these regulations increases income inequality. There are seven significant empirical papers in the literature that explore the impact of macroprudential regulations on inequality [23–30]. These studies have adopted the borrower-related instruments, such as the loan-to-value limit and debt-to-income ratio. Macroprudential policies were found to have a redistributive effect on wealth and income inequality through these measures [23, 26, 28, 30]. The study by Frost and van Stralen [26] further adopted the concentration and interbank exposure limits in their model, and this was found to increase inequality. However, the studies by Carpantier et al. [25] and Konstantinou et al. [27] argue that these macroprudential policies, through these measures, are helpful in reducing income inequality.

3. Research methods and data adopted for this study

The current study utilizes data covering the years 2000 to 2019. The main objective of the current study is to analyze the non-linear impact of economic development and income inequality in a group of 25 emerging markets that are grouped together based on their regions: 10 African countries, 8 Asian countries, and 7 European countries due to data unavailability in other countries. We focused on the period 2000–2019 in order to analyze how macroprudential instruments triggered the development-inequality relationship in these countries. Following Zungu et al. [9], we use GDP per capita in constant prices (US$) to capture economic development (ECD), while for income inequality, unlike in the study above, we take the argument into consideration that the Gini coefficient per country usually records small variations across time and is considered to be a relatively stable measure of inequality. Therefore, we use the pre-tax income held by the top 40% (PTII40%) and further pre-tax income held by the top 10% (PTII10%) collected from the World Inequality Database (Alvaredo et al.) [31] as a robustness model. Apart from those macroprudential policy instruments adopted by Zungu et al. [9], we control for FX and/or countercyclical reserve requirements (FXCRR), general countercyclical capital buffer/requirements (GCCBR), and a macroprudential index (0–12) (MI-12) in the model. We then control for capital-related (CRI) and borrower-related (BRI) instruments. Considering the ongoing debate on the inequality issue, some schools of thought further point to unconventional monetary policy as another source of income inequality. We then control for income composition, using an equity index (ICEI) and portfolio composition channels through house prices (PCCHP). The model controls for investments (INV), government expenditure (GE), trade openness (TRD) and tourism development (TORD). The variables were extracted from SWIID [32, 33] and Cerutti data (Cerutti et al.) [34].

3.1 Spatial lag panel smooth transition regression model

To evaluate the development-inequality relationship the SPSTR model, which is as an extension of the PSTR developed by González et al. [16], was used. The SPSTR model developed in this paper has been formulated as follows:

$$Gini40_{it} = \rho(WK)_{\mathrm{it}} + \beta_0 X'_{it} + \beta_1 X'_{it} g(q_{it}; \gamma, c) + \beta_2 A_{it} + \mu_i + \varepsilon_{it} \tag{3}$$
$$i = 1, \dots, N, \text{and } t = 1, \dots, T$$

where the subscript i, t indicates a $i - th$ cross-section and $i - th$ period, respectively, $GiniT40_{it}$ is the dependent variable, $K = (k_{11}, k_{21}, \dots, k_{\mathrm{N1}}, k_{12}, \dots k_{\mathrm{NT}})'$ is an $NT \times 1$ vector of dependent variables and W is a $NT \times \mathrm{NT}$ spatial weight matrix, A_{it} is a $k \times 1$ vector of independent variables (ECD, FXCRR, GCCBR, MI-12, CRI, BRI, ICEI, PCCHP, INV, GE, TRD and TORD), and β_0, β_1, β_2 are $k \times 1$ vectors of coefficients, whereas, μ_i represents the individual fixed effects, and the random errors term is denoted by ε_{it}. Following Granger and Teräsvirta [35], González et al. [16], we introduce the follows equation:

$$\varepsilon_{it} \sim N(O, \sigma^2), g(q_{it}; \gamma, c) = \left(1 + \exp\left(-\gamma \prod_{j=1}^{m} (q_{it} - cj)\right)\right)^{-1} \tag{4}$$

where Eq. (4) is a transition function and evidently, we have $0 < g(q_{it}; \gamma, c) < 1)$ where $c_j = (c_1, \dots, c_m)'$, $e = (1, 1, \dots 1)'$, is the $m \times 1$ vector of location parameters, and $\gamma > 0$ is a scale parameter. Without loss of generality, we set $m = 1$ to simplify mathematical deduction. Given i, the SLPSTR model can also be written as:

$$Y_i = \rho(WK)_{\mathrm{i}} + \beta_0 X'_i + \beta_1 G_i X'_i + \mu_i e + \varepsilon_i \tag{5}$$

where $Y_i = (y_{11}, y_{21}, \dots, y_{\mathrm{iT}}, \mathrm{e} = (1.1, \dots 1)'$ is a $T \times 1$ vector with all elements valued 1, $X_i = (x_{\mathrm{i1}}, x_{\mathrm{i2}}, \dots, y_{\mathrm{iT}}, G_i = \mathrm{diag}(g(q_{it}; \gamma, c), \dots, g(q_{iT}; \gamma, c))$, and $\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}, \dots, \varepsilon_{iT},)'$. Assuming that $Y = (Y'_1, Y'_2, \dots, Y'_N,)'$, $X = (X_1, X_2, \dots, X_N)'$, $E = (E'_1, E'_2, \dots, E'_N,)'$, where $E_i = (0, e, 0)$ is the $T \times N$ matrix in which the elements of the $i - th$ column are 1 and the other elements are 0, $G_i = \mathrm{diag}(G_1, G_2, \dots, G_N))$, $Z = (E \vdots X \vdots GX)$, $\Theta = (\mu_1, \mu_2, \dots, \mu_N, \beta'_O, \beta'_1)'$, and $\varepsilon = (\varepsilon'_1, \varepsilon'_2, \dots \varepsilon'_N)'$, then the two regimes of the SLPSTR model can be simplified as:

$$Y = \rho WK + Z\Theta + \varepsilon, \varepsilon \sim N(O, \sigma^2 I) \tag{6}$$

In the next section we will discuss the Bayesian estimation approach for model (6).

3.1.1 Building a Bayesian estimation for the PSTR model

We first construct the Bayesian analytical framework of model (4) before proceeding to the particular estimate phase. Given (γ, c), let $A = (I - \rho W)$, then the likelihood function of model (5) is:

$$L(Y|\Theta, \gamma, c, \sigma^2) \propto \sigma^{-NT} |A| \, exp \left\{ -\frac{1}{2\sigma^2} (AY - Z\Theta)'((AY - Z\Theta) \right. \tag{7}$$

The prior distribution of parameter ρ is usually assumed to be a uniform distribution with probability density function $\pi(\rho) = \frac{1}{\lambda_{max}^{-1} - \lambda_{min}^{-1}}$, where λ_{max}, λ_{min} are the maximum and minimum eigenvalues of a spatial weight matrix W, respectively, which indicates the $\rho \sim \left(\lambda_{min}^{-1}, \lambda_{max}^{-1}\right)$. The prior distribution of parameter Θ is set to be a multiple normal distribution $N(\mu_0, \Sigma_0)$, where μ_0 and Σ_0 are the prior expectation and covariance. We also assume the prior distribution of parameter σ^2 to be an inverse gamma distribution $IG(\mu_0, \Sigma_0)$, and set prior γ and c as gamma distribution and normal distribution, that is $\gamma \sim G(a, b)$,$(c \sim N(\mu_c, \Sigma_c)$. Combining all the priors with a likelihood function, we can obtain the joint distribution of all variables as follows:

$$P\left(Y, \rho, \Theta, \gamma, c, \sigma^2\right) = L\left(Y|\rho, \Theta, \gamma, c, \sigma^2\right).\pi(\rho).\pi(\Theta).\pi(\gamma).\pi(c).\pi\left(\sigma^2\right) \tag{8}$$

where $\pi(.)$ denotes the prior probability density function of each parameter. According to the Bayesian theorem, the joint posterior distribution of all parameters is given by:

$$P\left(\rho, \Theta, \gamma, c, \sigma^2\right) \triangleq P\left(\rho, \Theta, \gamma, c, \sigma^2|Y\right) \tag{9}$$

On the basis of a joint distribution and joint posterior distribution, we can get the conditional posterior distribution of each parameter as follows:

$$P\left(\Theta|\rho, \gamma, c, \sigma^2\right) \propto N(\mu, \Sigma) \tag{10}$$

where $\mu = \left(Z'Z + \sigma^2 \sum_0^{-1}\right)^{-1} \mu = \left(Z'AY + \sigma^2 \sum_0^{-1} \mu_0\right)$ It can be seen from Eq. (10) that the conditional posterior distribution of Θ is a multiple normal distribution when given other parameters. Similarly, the conditional posterior distributions of other parameters are as follows

$$P\left(\sigma^2|\rho, \Theta, \gamma, c\right) \propto IG\left(\frac{NT}{2}\right) \propto, \frac{(AY - Z\Theta)'(AY - Z\Theta)}{2} + \beta) \tag{11}$$

$$P\left(\Theta|\rho, \gamma, c, \sigma^2\right) \propto |A\ (\rho)|\, exp\left\{-\frac{1}{2\sigma^2}(A(\rho)Y - Z\Theta)'(A(\rho)(Y - Z\Theta).\frac{1}{\lambda_{max}^{-1} - \lambda_{min}^{-1}}\right. \tag{12}$$

$$P\left(\gamma, c|\Theta, \rho, \sigma^2\right) \propto exp\left\{-\frac{1}{2\sigma^2}(AY - Z\Theta)'((AY - Z\Theta).\pi(\gamma).\pi(c)\right. \tag{13}$$

where $A(\rho) = (I—\rho W)$. From the conditional posterior distributions of all parameters, we can see that the probability density functions of γ,$\boldsymbol{c}$ and ρ are more complex, and these parameters cannot be directly sampled. Therefore, we use the Metropolis-Hastings algorithm to deal with this problem. Assuming that the current value of ρ is ρ_t, that meets $P(\rho_t|\Theta, \gamma, c, \sigma^2) > 0$, and the candidate value ρ^* is generated from the proposed distribution $F(\rho^* \mid \rho_t) = f(\rho^* - \rho)$, where $f\ (.)$ is the probability density function, the transfer process is $\rho^* = \rho_t + \lambda z$, where $z \sim N(0, I)$, and λ is a transfer parameter. Then the reception ratio of ρ^* *is* $A_i(\rho^* \mid \rho_t) = \min\{1, R_1\}$, where

$$R_1 = \frac{P(\rho^*|\Theta, \gamma, c, \sigma^2) F(\rho_t|\rho^*)}{P(\rho_t|\Theta, \gamma, c, \sigma^2)\, F(\rho^* \mid \rho_t)} \tag{14}$$

Similarly, assuming that the current values of (γ, c) are (γ_t, c_t), and the candidate values (γ^*, c^*) are generated from the proposed distribution $\gamma^* \sim N\left(\gamma_t, {\sigma^2}_y\right)$ and $c^* \sim N(c_t, {\sigma^2}_c I)$, respectively, then the reception ratio of (γ^*, c^*) is $A_2((\gamma^*, c^*)|\gamma_t, c_t)) = \min\{1, R_2\}$, where in:

$$R_2 = \frac{P((\gamma^*, c^* | \rho, \Theta, \sigma^2) f_\gamma \left(\gamma_t | \gamma^*, \sigma_y^2)\right) \left(f_c(c_t | c^*, \sigma_c^2)\right)}{P((\gamma_t{}^*, c_t{}^* | \rho, \Theta, \sigma^2) f_\gamma \left(\gamma^* | \gamma_t, \sigma_y^2)\right) \left(f_c(c^* | c_t, \sigma_c^2)\right)} \tag{15}$$

$f_\gamma\left(\gamma_t|\gamma^*, \sigma_y^2)\right)$ represents the normal distribution probability density function of $\gamma_t$with mathematical expectation γ^* and variance $\sigma_y^2 f_c\left((c_t|c^*, \sigma_c^2)\right)$ denoting the normal distribution probability density function of c_t with mathematical expectation c^*, and variance σ_c^2. σ_c^2 and σ_y^2 are adjustment parameters. Z^* and Z_t indicate the value of Z at a corresponding time, when the value of $(\gamma, c)$are(γ^*, c^*) and γ_t,c_t, (respectively)

Firstly, we employ the Gibbs sampling method to generate parameters $\boldsymbol{\Theta}$ and σ^2 based on their conditional posterior distributions. Then we sample parameters ρ,γ and $\boldsymbol{c}$ by using the Metropolis-Hastings algorithm. Specifically, the Bayesian estimation procedure of the SLPSTR model is as follows: (1) Set the initial values of parameters $(\rho, \Theta, \gamma, c, \sigma^2)$ to be $(\rho_0, \Theta_0, \gamma_0, c_0, {\sigma_0}^2)$, and let $(\rho_t, \Theta_t, \gamma_t, c_t, {\sigma_t}^2)$ be the results of t—th sampling. (2) Sample Θ_{t+1} from the conditional distribution $P(\Theta|\rho_t, \gamma_t, c_t, {\sigma_t}^2)$. (3) Sample ${\sigma^2}_{t+1}$from the conditional distribution $P(\sigma^2|\rho_t, \gamma_t, c_t, \Theta_{t+1})$;. (4) Generate random number r from uniform distribution $U(0, 1)$, firstly, and then generate (ρ^*, γ^*, c^*) from the following random process: $\rho^* = \rho_t + \lambda z$, the normal distribution $N(\gamma_t, {\sigma^2}_y)$ and the normal distribution $N(c_t, \sigma^2, {}_cI)$, respectively, based on which we obtain $(\rho_{t+1}, \gamma_{t+1}, c_{t+1})$ defined as:

$$\rho_{t+1} = \begin{cases} \rho^*, & \text{if } r < A_1 = \min\{1, R_1\} \\ \rho_t, & \text{others} \end{cases} \tag{16}$$

$$(\gamma_{t+1}, c_{t+1}) = \begin{cases} (\gamma^*, c^*), & \text{if } r < A_2 = \min\{1, R_2\} \\ (\gamma_t, c_t), & \text{others} \end{cases} \tag{17}$$

5) Let $t = t + 1$ and repeat step (ii)—(iv) until convergence. The convergence criterion

$$\frac{\|\rho_t, \gamma_t, c_t, {\sigma_t}^2\|}{\|\rho_{t-1}, \Theta_{t+1}, \gamma_{t-1}, c_{t-1}, {\sigma_{t-1}}^2\|} < \alpha \tag{18}$$

is used in the process of estimation, where $\|.\|$ represents the Euclidean norm and a is an accuracy requirement.

4. Analysis of the study

4.1 The results of the testing procedure of the BSPSTR model

We considered all variables (ECD, FXCRR, GCCBR, MI-12, CRI, BRI, ICEI, PCCHP, INV, GE, TRD and TORD) as candidates for determining the suitable transition variable, following González et al. [16]. The results of all the testing stages of the BSPSTR for all regions are reported in **Table 1**. The first column of **Table 1** shows the results of the appropriate transition for our model. The results for all regimes signify that ECD is the best suitable choice of transition variable, as the p-values of both the LM_X (4.583e−10, 7.968e−18 and 8.167e−17), and LM_F (5.897e−9, 7.450e−12 and

Region	Test	Transition Variable ECD			Results of the H_0	Selecting Order m		
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 1; H_{01}^*$	$m = 1; H_{02}^*$	$m = 1; H_{03}^*$
AEM	LM_F	15.06	13.58	12.04	15.06	0.88	7.01	12.50
		4.583e−10	3.192e−05	2.062e−06	4.583e−10	7.302e−05	0.9978	1.226e−03
	LM_χ	28.30	20.88	15.96	28.30	3.59	40.86	30.81
		5.897e−16	4.123e−7	2.347e−12	5.897e−9	2.564e−110	0.5986	2.678e−9
	WB	—	—	—	0.00	3.12	7.84	10.59
	WCB	—	—	—	0.00	0.00	0.6060	0.00
EAM	LM_F	30.40	10.70	14.28	30.40	20.89	4.01	14.60
		7.968e−18	0.00	4.998e−18	7.968e−18	4.142e−15	0.700	0.00
	LM_χ	60.90	41.38	20.98	60.90	20.59	6.86	30.81
		7.450e−12	5.675e−08	3.296e−06	7.450e−12	2.237e−10	0.896	4.678e−7
	WB	—	—	—	0.00	14.35	0.76	6.90
	WCB	—	—	—	0.00	0.000	0.00	0.00
EEM	LM_F	44.90	15.65	10.30	44.90	32.54	0.54	13.09
		8.167e−17	3.945e−05	4.698e−08	8.167e−17	8.997e−07	0.879	2.112e−04
	LM_χ	20.18	14.89	12.12	20.18	20.86	0.70	19.84
		6.258e−13	5.567e−09	3.479e−06	6.258e−13	6.790e−09	0.956	3.926e−10
	WB	—	—	—	0.00	9.70	0.80	9.60
	WCB	—	—	—	0.00	0.00	0.60	0.00

The PTII40% is the dependent variable. Using the LM-type test, all variables as mentioned in section 4.1 were considered as possibilities for determining the proper transition variable. The p-values are denoted by p-v, while the F-statistic is denoted by Fs. AEM stands for African Emerging Markets, while EAM stands for Emerging Asian Markets and EEM stands for Emerging European Markets.
***Source:** Author's calculation based on World Development Indicators [33] data.*

Table 1.
Results of the testing stages of the BSPSTR model.

7.450e−12), respectively, are smaller compared to other variables included as candidates. The homogeneity test results are then provided in the second column. To test the null hypothesis of the linearity, we calculate F-statistics corresponding with their p-values for both LM_F and LM_X. For a robustness check of the nonlinearity test, the p-values of both the WCB and WB were generated. The rejection of the null hypothesis of linearity was confirmed as the p-value of both the LM_F (4.583e−10, 7.968e−18, 8.167e−17), and LM_X (5.897e−9, 7.450e−12, 6.258e−13) confirmed the evidence of the nonlinearity between economic development and income inequality in all regions included in this study, respectively. The results were further supported by the WB and WCB as they indicated the existence of the remaining non-linearity between the two variables. The findings on homogeneity are consistent with those of [4, 6, 8, 9, 13, 17–19, 36].

Finally, the third column of **Table 1** contains the sequence for selecting order m in BSPSTR, which is critical for this study because it aims to determine whether the nature of the development inequality relationship is characterized by one transition, as explained by the Kuznets hypothesis, or by more than two transitions, as explained by the Tribble hypothesis. The results for all regions show the feasibility of the second transition of economic development as the results of both the LM_F and LM_X rejected H_0, indicating that, when ECD was chosen as the optimal transition variable, our model was characterized by two transitions, those divided by high and low levels of economic development for these regions. Our findings are in line with results documented by Shahbaz, Theyson and Heller [12, 13]. However, to avoid misleading results, validating the results of the order of the transition is crucial for BSPSTR using the WCB and WB, as in Teräsvirta [37].

4.2 Model evaluation and the estimated threshold of the BSPSTR model

The results of the model evaluation and the estimated threshold of our model are reported in this section. Following Eitrheim and Teräsvirta [38], we first examined the reliability of choosing $m = 2$ for all regions as the optimum transition variable for our model, using two kinds of misspecification tests: no remaining non-linearity (NRN) and parameter consistency (PC) [16]. **Table 2** displays the results of the NRN, PC, and the projected threshold. The p-values of the LM_F and LM_χ for parameter constancy indicate that the parameters are constant, while the second section of **Table 2** displays the results of both the WB and WCB tests, which account for both heteroskedasticity and possible within-cluster dependence, indicating that the estimated model with two transitions is adequate as our model. Finally, the last portion of **Table 2** presents the estimated threshold for our first and second transition.

Region	Test	Parameter Constancy	No Remaining Nonlinearity	Transition two	
				Second threshold	
AEM	LM_F	10.918 (0.00)	—	c	US$15900*** (20.99)
	LM_χ	20.573 (0.00)	—	γ	13.23*** (3.01)
	WB		1 (p-va)		—
	WCB		1 (p-va)		—
EAM	LM_F	15.121(0.00)	—	c	US$17078*** (9.94)
	LM_χ	32.998 (0.00)	—	γ	15.98*** (1.54)
	WB	1 (p-va)	1 (p-va)		—
	WCB	1 (p-va)	1 (p-va)		—
EEM	LM_F	9.987 (0.00)	—	c	US$16,800*** (10.23)
	LM_χ	39.209 (0.00)	—	γ	18.89*** (3.76)
	WB		1 (p-va)		—
	WCB		1 (p-va)		—

*The PTII40% is the dependent variable. *** representing the 1% level of significance. AEM is an abbreviation for African emerging markets, EAM is an abbreviation for emerging Asian markets, and EEM is an abbreviation for Emerging European Markets.*
Source: *Author's calculation based on World Development Indicators [33] data.*

Table 2.
Results of the evaluation test and the estimated threshold.

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The current study adds a very significant contribution to the literature as it shows that all these regions are experiencing the second transition of economic development. The results show that these regions are at the beginning of the second transition with an estimated economic development threshold found to be US$15900 for AEM, US $17,078 for EAM and US$19,000 for EEM. However, the nature of the relationship in these regions varies as per the region. For instance, AEM is characterized by the inverted U-shape, while EAM and EEM are characterized by a U-shape relationship.

The estimated threshold for AEM illustrates that, in the first regime of the second transition of development, when the degree of economic development is below US $15,900, it tends to benefit a few individuals in the economy, which raises income inequality. Thus, during periods of poor economic development and high inequality, growing inequality may reduce the professional opportunities available to society's most disadvantaged groups, diminishing social mobility and the economy's growth potential. However, when the degree of development exceeds US$15,900, strong economic development implies an improvement in human capital, such as skills, education, and training, as well as increased investment in physical capital, such as machinery, factories, and roads. This will result in less economic inequality. For EAM and EEM, on the other hand, it illustrates that once the level of economic development is above the estimated threshold (US$17,078 and US$19,000) for these regions, it will no longer benefit everyone in the economy, but it will tend to increase inequality by benefiting only some individuals. These findings can be interpreted as follows: A high level of development goes hand in hand with high investment in both physical capital and skills. Thus, if these kinds of investments are channeled to only certain individuals, that would raise income inequality. Moreover, those counties below the estimated threshold could attain a high level of development through investing more in technology, the banking system, trade, foreign investments, loans to the region and a strong labor market.

To obtain a clear picture of which countries within these regions are at the lower/ higher ends of the Tribble hypothesis of economic development and income inequality, the mean GDP per capita was calculated as a proxy for economic development. **Figure 1** illustrates that, with the exception of Korea, Republic., which has a mean of US$24967 in EAM, practically all the countries are at the lower end of economic development in the second transition below the estimated threshold.

Several factors that might drive these regions to be in the second transition of economic development, but at the lower end of the Tribble curve, for example, are distinguished by rapid growth, which is fueled by factors such as technology, the banking system, trade, foreign investment, loans to the region, a strong labor market, and improvements in the services and agricultural sectors. Improvements abound to reduce poverty and income inequality.

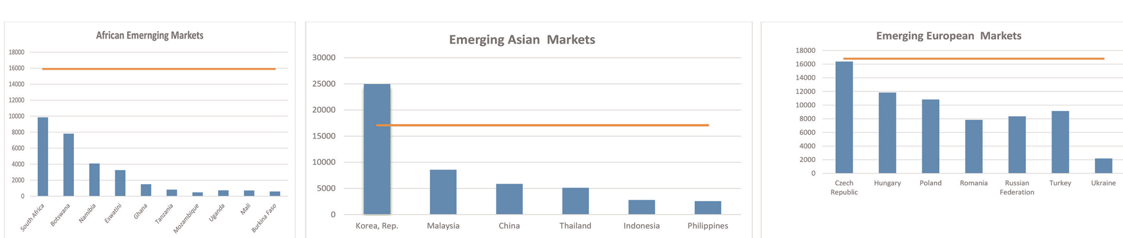

Figure 1.
The mean Gini coefficient for emerging economies. Source: Author's calculation based on SWIID data [32].

4.3 Empirical results of the BSPSTR for all regions

The generated results for all regions are reported in **Table 3**. The results differ based on the region in which the countries are located, so the results reported in AEM differ from those of EAM and EEM. The BSPSTR model reveals that, for the AEM, the direct economic development effect on income inequality, as measured by β_{0j}, is positive and significant; while for both the EAM and EEM, the impact in the low regime β_{0j}, is negative and significant. As reported in **Table 1**, the results confirm the homogeneity test: the effects of economic development on income inequality seem to be strongly non-linear. In fact, the coefficient of the non-linear component of the model, β_{1j}, for AEM is positive and highly significant, while for EAM and EEM it is negative and highly statistically significant.

As a result, the influence of economic development on income inequality is conditional to the degree of development. As the level of economic development varies from low to high, this suggests that changes in inequality with reference to economic development vary from $\beta_{0j} + \beta_{1j}$. The transition between these extreme regimes occurs at the endogenous location parameter c. The magnitude coefficient of ECD is found to have a massive impact on income inequality during a high level of development above the threshold, in AEM and EEM, while for EAM it is found to have a massive impact below the threshold. For AEM and EEM it is found to be 7.03 and 5.40 respectively. While for EAM it is found to be 5.30.

The results make a very significant contribution towards understanding the dynamic impact of development inequality in emerging economies, especially during the macroprudential policy regime. As our study builds on the argument documented by Chiu and Lee [5], who classified 59 countries into 32 high-income countries and 27 low-income countries, and Zungu et al. [9], who built a panel of 15 emerging countries. Both of these studies claim that the nature of development inequality in emerging economies is explained by the inverted U-shape relationship. However, after combining the advantage of the PSTR with spatial correlation and a Bayesian approach, following Li et al. [17], we found that emerging economies are in the second phase of the transition, as is evident by the LM_F and LM_X results in **Table 1** (raw 3). The explanation of our findings could be that the results from the existing studies were triggered by the estimation techniques and the level of the countries included in the model. Moreover, this could also be due to the fact that studies on this subject matter, especially those that investigated this problem in a panel-data framework, having introduced time and cross-sectional effects to represent individual heterogeneity, then satisfy the assumption that the coefficients of explanatory variables are assumed to be constant for all section units and periods. The results further support the evidence that the locations of the countries might also have impacted the existing literature, as the results for AEM and EEM are different from those for EAM. This finding is consistent with previous empirical studies that demonstrated a substantial positive and negative effect of economic development on income inequality, such as [5–7, 9, 13, 19]; as well as those that found a negative and positive effect [5, 10, 11] and those studies that found the existence of two transitions of economic development [12, 13] that support the existence of a Tribble S-shape. The explanation underlying the AEM results could be that income growth promotes inequality in a low-development regime, but economic prosperity increases inequality among individuals in a high-development regime. For EAM and EEM, on the other hand, income growth generates inequality in a high-development regime, while when the economic

Vari	Model I: Africa Emerging Markets (AEM)		Model II: Emerging Asian Markets (EAM)		Model III: Emerging European Markets (EEM)	
	$\mathbf{LR}\beta_{0j} \times \mathbf{100}$	$\mathbf{HR}\left(\beta_{0j}+\beta_{1j}\right) \times \mathbf{100}$	$\mathbf{LR}\beta_{0j} \times \mathbf{100}$	$\mathbf{HR}\left(\beta_{0j}+\beta_{1j}\right) \times \mathbf{100}$	$\mathbf{LR}\beta_{0j} \times \mathbf{100}$	$\mathbf{HR}\left(\beta_{0j}+\beta_{1j}\right) \times \mathbf{100}$
ECD	3.90(0.19)***	−7.03(0.19)***	−1.30(0.99)**	5.30(0.99)***	−5.40(0.81)**	1.98(0.10)**
CRR	1.18(0.46)**	0.71(0.23)**	1.18(0.46)**	0.71(0.23)**	1.18(0.46)**	0.71(0.23)**
GBR	5.72(1.13)**	1.80(2.00)	5.72**(1.13)	0.10(0.67)	5.72**(1.13)	2.01(0.09)***
CRI	1.18(0.46)**	−0.71(0.23)**	−1.59(0.30)**	0.89(0.15)**	−0.71(0.23)**	−0.71(0.23)**
BRI	−5.00(1.10**	2.20(0.99)**	−3.70(0.99)***	1.98(0.20)**	−2.20(0.43)	4.20(1.88)
ICEI	1.23(0.37)**	2.19(0.70)**	1.89(0.80)**	2.57(0.50)**	−2.98(1.21)**	3.10(0.40**
PCHP	1.09(0.10)***	0.11(0.02)**	2.29(0.99)**	1.39(0.69)**	0.70(0.90)	−2.70(0.70)**
INVM	−0.31(0.02)***	−0.62(0.03)***	−2.93(0.99)***	1.45(0.49)**	−2.20(1.01)**	−4.05(0.90)**
TOD	−1.30(0.12)**	5.11(0.12)***	−2.29(0.99)**	−3.39(0.69)*	0.70(0.09)**	−2.70(0.70)**
GE	−2.10(0.15)***	0.11(0.02)**	−2.29(0.99)**	−1.39(0.69)**	−0.70(0.90)**	2.70(0.70)**
Dum	Yes	No	No	No	Yes	No
γ	US$15900*** (20.99)		US$17078*** (9.94)		US$19,000*** (10.23)	
c	13.23** (3.01)		15.98*** (1.54)		18.89** (3.76)	
Stand d	0.01456		0.08950		0.02101	
# of obs.	200		120		140	
# of cou	10		6		7	

*Note: The dependent variable is the Gini coefficient. The numbers in brackets denote the standard errors obtained by using the cluster-robust and heteroskedasticity-consistent covariance estimators, allowing for error dependency within individual countries. ***, **, and * reflect the 1, 5, 10% levels of significance, respectively. ESD denotes the estimated standard deviation (residuals), p-v are the p-values, and H is Hansen. LR and HR stand for low regime and high regime, respectively.*
Source: *Author's calculation based on World Development Indicators [33] data.*

Table 3.
Development inequality; BSPSTR, for African, Asian and European emerging markets.

development is within the projected threshold in the second transition, inequality among the population in these regions decreases. This might be because policy action in the two regimes (low and high) favors different groups. During a recession, for example, government intervention through spending may promote consumer consumption, but in the higher regime it may benefit investors. One of the main objectives of this study was to find out how macroprudential policy instruments triggered the development inequality relationship in three adopted emerging economies, following Zungu et al. [9]. Unlike the policy instruments adopted in their study, the current study extended their model by including countercyclical reserve requirements, general countercyclical capital buffer/requirements, and a macroprudential index (0–12). Countercyclical reserve requirements (CRR) in all regions have a statistically positive impact on income inequality in both regimes. This shows that policy tightening in CRR requirements is bad for income inequality at both the high and low levels of development. Similar to CRR, the General countercyclical capital buffer/requirement (GCCBR) was found to increase income inequality in all regions in both the low and high regimes of development.

For AEM and EAM, capital-related instruments (BRI) have a statistically positive impact on income inequality in the low regime of development, while for EEM they have a negative impact. Then, in the high regime, it is negative in AEM and EEM and statistically significant, while for EAM it has a positive impact. The results are supported by Frost and Stralen [26]. A borrower-related instrument (BOR) has a statistically positive effect on income inequality in all regions during the low regime of development, but has a negative impact during the high regime. This demonstrates that tightening loan-to-debt and debt-to-income ratios is detrimental to income disparity at low levels of development, but beneficial at high levels of development.

Following the argument documented by Zungu and Greyling [39] and others, we extended the development-inequality arguments by controlling for monetary policy through unconventional tools. We incorporated two unconventional monetary policy channels in our model: income composition captured by the equity index (ICEI) and portfolio composition captured by housing prices (PCCHP). Unconventional monetary policy in both channels was shown to raise income inequality in all regions, at both the low and high levels of development. Our findings show that rising house prices laid the path for a housing affordability problem, while also increasing homeowners' wealth. This backs up the findings of Gibson et al. [40], Gibson et al. [40] and Filandri and Olagnero [41]. In terms of income distribution, investment appears to be a significant indicator. This is because INVM has a negative and statistically significant influence on income inequality in both regimes in all regions. The findings confirmed those of Blonigen and Slaughter [42] for the United States and Figini and Görg [43] for 100 developed and developing economies. Theoretically, the argument for the negative impact is that an increase in capital investment causes some goods to be produced that are not immediately consumed, but are instead used to produce other goods as capital goods, leading to an increase in economic growth and, consequently, a decrease in inequality [44].

Considering the nature of the countries being examined in this study and tourism that might trigger the development-inequality relationship, we then extended the development-inequality relationship by controlling for tourism development (TOD), as captured by the number of arrivals of international tourists. Incera and Fernández [45] expanded on this even further by stating that high-income households enjoy a higher benefit from tourism than low-income ones. This was thought to trigger development-inequality, as high levels of tourism development are linked to high levels of growth and economic development. In all regions, TOD has a negative and statistically relevant impact on income inequality, while at a high level of development, it becomes positive and statistically significant, showing that it promotes inequality in all regions, except for EAM. The results are empirically plausible, with results documented by Incera and Fernández [45] for Galicia, Alamand and Paramati [46] for a panel of developing economies, and Fang et al. [47] for a panel of developed and developing countries.

Finally, we then controlled for the redistribution of income by including government expenditure as a fiscal policy instance. Across all the adopted regions the fiscal policy instance through government expenditure was found to have a negative impact on income inequality, at the low level of economic development, while at the high level of economic development GE was found to have a positive impact on inequality, except for Emerging European Markets where it is negative and statistically significant. This empirical result is consistent with the findings of Zungu et al. [48] in the SADC area. They also emphasize in their paper that there is a serious debate over whether government spending plays a significant role in declining/increasing income inequality; as they point out, Tanzi [49] argues that government spending does nothing to reduce income inequality, but may even worsen it.

4.4 Sensitivity analysis and robustness checks

The data indicates that the impact of economic development on income inequality is non-linear in the three emerging regions investigated, regardless of the variable used to measure the inequality. We used the pre-tax income of the top 10% (PTI10%) from the World Inequality Database Alvaredo et al. [31] to measure income inequality. The variables are defined in the same way as in the baseline methodology. In this part, we provide further evidence of the robustness of these results. **Table 4** contains the findings of the robustness assessments for all the regions covered in this study. Again, all of the models' testing methods were followed. We further tested whether our findings were sensitive to additional control variables. We controlled for a macroprudential index (0–12) (MI-12) given the availability of the combination index of 12 macroprudential regulations.

Model IV: AEM	**PTII10% = 4.00ECD*** + 3.89CRR** + 0.65GBR**-3.33CRI*** + 5.74MI-12**-3.44BRI* + 5.68ICEI + -5.65PCHP**-2.00PINV**-4.10TOD**-2.00GE** [15.00$_{\gamma}^{**}$,14 800$_{C}^{***}$]- 3.02ECD*** + 3.89CRR** + 3.65GBR + 3.33CRI*-5.74MI-12** + 2.02BRI** + 3.11ICEI** + 2.34PCHP**-1.09PINV** + 0.10TOD** + 2.30GE****
Model V: EAM	PTII10% = −2.24ECD*** + 2.12CRR** + 0.98GBR**-1.23CRI*-3.89MI-12** + 4.91BRI** + 2.30ICEI**-4.86PCHP***-3.20PINV**-2.32TOD**-2.02GE** [11.25$_{\gamma}^{**}$,17 500$_{C}^{***}$]+ 4.10ECD*** + 3.90CRR** + 1.65GBR + 2.01CRI* + 2.12MI-12**-2.04BRI**-1.92ICEI**-3.00PCHP**-0.92PINV**-1.22TOD** + 2.02GE**
Model VI: EEM	PTII10% = −1.02ECD*** + 2.811RR*** + 0.65GBR**-2.44CRI**-4.20MI-12**-2.19BRI** + 0.92ICEI**-3.34PCHP**-2.92PINV**-1.02TOD** + 3.03GE** [14.04$_{\gamma}^{**}$,18 400$_{C}^{***}$]+ 2.11ECD*** + 4.94CRR* + 2.91GBR**-2.01CRI* + 2.92MI-12**-0.88BRI +3.73ICEI**-4.00PCHP**-2.30PINV**-2.77TOD** + 0.90GE***

*The ***/**/* denote the levels of significance at 1, 5 and 10%, respectively.*
***Source**: Author's calculation results based on [33].*

Table 4.
Development inequality: Robustness checks model.

This was undertaken to see whether the results obtained in the baseline methodology were sensitive to the variables used as control variables. The estimated results indicated that the non-linear impact of economic development on income inequality was unaffected by the inequality-measurement or control variables utilized. Indeed, the results were remarkably comparable to those obtained initially. We find that when controlling for macroprudential policy instruments, the macroprudential index (0–12) (MI–12) enhances income inequality at low levels of development while decreasing income inequality at high levels of development in all regions.

5. Conclusion and policy recommendations

The existing empirical literature is marked by controversy surrounding the nature of the development-inequality relationship in both advanced and emerging markets. The current paper seeks to fill the existing inconclusive situation in both theoretical and empirical ways by examining the current subject in emerging economies, focusing on the prudential policy region; in a nutshell, by examining how the adopted macroprudential and unconventional monetary policies during the financial crisis triggered the development-inequality relationship in these regions. As it has been noted in the literature, the estimation techniques or the level of the economy being studied when examining the development-inequality relationship were believed to trigger the existing results in these subject matters. Studies that have investigated this problem in a panel data framework, have introduced time and cross-sectional effects to represent individual heterogeneity, which then satisfy the assumption that the coefficients of the explanatory variables are assumed to be constant for all section units and periods. However, in practice, this assumption is sometimes unreasonable. For instance, the model adopted by Zungu et al. [9] actually allows coefficients to change with cross sections and times, which is a sufficient relaxation of the heterogeneity assumption in panel data models. Consider a scenario in which the local equilibrium prices of all local markets are correlated in the general equilibrium model; individuals in the network model are interconnected; and in a competitive market, one participant's decision is influenced by the decisions of other participants, and so on. The classic econometric model will no longer be applicable when dealing with the aforementioned study areas. Then the spatial method plays a significant role in such a problem.

The current study seeks to address these issues by separating countries based on their region, focusing on those that are emerging countries from Africa, Asian and European economies. The primary objective behind categorizing these countries by their respective regions was to compare and track if the correlation between the variables of interest is substantially impacted by the country's location. We therefore establish a model for the emerging market by extending the PSTR model developed by González et al. [16] to account for spatial correlation between variables, and we also construct a Bayesian inference for the PSTR model. The estimation results strongly support the presence of non-linearity in the relationship between economic development and income inequality in these regions. The current study adds a very significant contribution to the literature as it shows that all these regions are experiencing the second transition of economic development. The results show that these regions are at the beginning of the second transition, with an estimated economic development threshold found to be US$15900 for AEM, US$17078 for EAM, and US$19000 for EEM. However, the nature of the relationship in these regions varies as per the region.

For instance, AEM is characterized by the inverted U-shape, while EAM and EEM are characterized by a U-shape relationship.

We further seek to find out how macroprudential policy instruments trigger the development-inequality relationship in these regions by cooperating with five types of macroprudential policy instruments; countercyclical reserve requirements, a general countercyclical capital buffer/requirement, and a capital-related, borrower-related, and macroprudential index (0–12) in the model. Adopting macroprudential policies, such as countercyclical reserve requirements and a general countercyclical capital buffer/requirement, was found to improve inequality in all regions for both regimes, while the second group of these policy instruments was found to improve inequality in the lower regime in AEM, while for EAM and EEM, it was found to decrease inequality; then decreasing income inequality in the high regime in AEM and EEM while increasing inequality in EAM countries. At low levels of development, capital-related and borrower-related instruments were found to improve income inequality at low levels of development while reducing inequality above a certain threshold. While borrower-related instruments were found to reduce inequality in low regimes, they improved inequality above the estimated threshold. Considering the argument made by Zungu and Greyling [39], we included unconventional monetary policies in our model to trace how the adoption of these policies triggered the development-inequality relationship in these regions. Unconventional monetary policy was found to improve income inequality in these regions. More interestingly, investment, tourism, and trade openness were found to reduce income inequality in these regions.

From a policy standpoint, our findings may have a variety of policy ramifications. Firstly, the presence of the second transition of development-inequality and the economic development threshold calls into question the effectiveness of distribution policies and the effects of GDP per capita on reducing inequality. Secondly, macroprudential regulation, particularly foreign exchange and/or countercyclical reserve requirements, as well as general countercyclical capital buffer requirements, should be monitored when implemented in these regions as they appear to increase income inequality. Thirdly, policy-makers should be cautious when implementing unconventional monetary policies as they are found to contribute to high inequality by reducing per capita income. Fourthly, government policies to increase agricultural productivity through land redistribution, investment, trade, subsidies, the provision of public goods for agriculture, promoting a successful labor market regime, and for human development are significant for these countries. Fifthly, all these countries are situated below the estimated threshold except for Korea, Republic are encouraged to work towards formulating policies that aim to increase agricultural productivity through land redistribution, attract investment, improve trade, provide public goods for agriculture, promote successful labour market regimes, and for human development. That will trigger an increase in the level of GDP per capita and reduce inequality.

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