BAREKENG: Journal of Mathematics and Its Applications
December 2023 Volume 17 Issue 4 Page 2225–2234
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol17iss4pp2225-2234

A DYNAMIC HETEROGENEOUS NEXUS BETWEEN PADDY AND POVERTY: EVIDENCE FROM DUMITRESCU-HURLIN CAUSALITY AND PMG-ARDL

Mohamad Egi Destiartono[1*]

[1]*Department of Economics, Faculty of Economics and Business, Diponegoro University*
St.. Prof. Soedarto, SH Tembalang, Semarang, 50272, Indonesia

Corresponding author's e-mail: * ***medestiartono@lecturer.undip.ac.id***

Article History:

Received: 21st July 2023
Revised: 7th October 2023
Accepted: 6th November 2023

Keywords:

PMG, Dumitrescu-Hurlin;
Causality;
Paddy;
Poverty.

ABSTRACT

Agriculture is supposed to have a pivotal role in assisting poverty alleviation in Indonesia. Hence, this paper empirically examines the causal link between paddy productivity and poverty rates in Sumatra, retrieving balanced panel data from ten provinces for the period 2010-2022. Dumitrescu-Hurlin (DH) causality and Pooled Mean Group (PMG) methods are applied in order to reveal the causal direction and the elasticity under heterogeneous panel models. This paper integrates slope homogeneity, panel unit root, and panel cointegration tests. The results reveal that poverty rates and paddy productivity, are integrated in mixed order, $I(0)$ and $I(1)$, and they are cointegrated. The DH causality test denotes a unidirectional causality from paddy productivity toward poverty rates which implies the absence of a feedback effect. Following the PMG model, there is a positive impact of paddy productivity on poverty rates in the short run ($\Delta\beta$= 0.29); however, this linkage switches to become negative in the long run (β= -0.48). A 1% improvement in paddy productivity will be followed by a 0.48% reduction in poverty rates. Thus, augmenting paddy productivity has a favorable role in declining poverty rates. The estimated parameters of long-run PMG are robust, i.e., consistent with alternative methods of cointegrated regressions.

How to cite this article:

M. E. Destiartono., "A DYNAMIC HETEROGENEOUS NEXUS BETWEEN PADDY AND POVERTY: EVIDENCE FROM DUMITRESCU-HURLIN CAUSALITY AND PMG-ARDL," *BAREKENG: J. Math. & App.*, vol. 17, iss. 4, pp. 2225-2234, December, 2023.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

The nexus between agriculture sub-sectors and poverty in developing countries such as Indonesia is a pivotal topic to be investigated. Empirical findings in this area of research can be insight for policymakers in order to promote necessary programs and policies in agriculture sectors (e.g., subsidies, insurance, agriculture infrastructure investment, and credits) that have the feasibility to enhance farm productivity. It is supposed that augmenting agricultural productivity has a significant impact on income and poverty rates [1]. A previous study noted that the impact of agriculture on poverty alleviation is strong in rural areas [2]. More specifically, the farming sub-sector of paddy has a vigorous role in sustaining households' welfare since it supplies staple food. Paddy is the main source of nutrients and calories for the majority of households in Southeast Asia [3]. Consequently, distress in paddy production will cause shocks in rice stocks and prices. The bad tidings are that the current rice farming faces crucial challenges due to rapid population growth, lack of labor, inefficient fertilizer use, and climate change [4][5].

Numerous papers noted that the beneficial impact of agricultural productivity on poverty alleviation in developing countries is confirmed [5][6][7]. Enhancing paddy production has a pivotal role in assisting food security and poverty eradication through various pathways [7]. Foremost, an increase in paddy productivity leads to an improvement in farms' profits. This chain rule refers to the technical efficiency effect and it is more proper for reducing rural poverty. Furthermore, the yield of paddy capacity needs to be sufficient with respect to the demand for rice in order to support food security and affordable rice prices [8]. This chain rule has a favorable impact on reducing both rural and urban poverty.

Although the remarkable benefit of agricultural productivity in poverty alleviation is widely discussed, the causal connection between them is under debate. Financial constraints lessen the physical and cognitive of employees through nutritional deficiencies, low years of schooling, and poor health status, which in turn simultaneously affect their productivity [9]. In other words, an increase in poverty rates causes a reduction in the number of productive workers which in turn declines the agricultural output per worker. Instead of a one-way causal nexus, there is a possible bidirectional causality between paddy and poverty.

It is widely known that paddy is a politically and socially strategic commodity in Indonesia since white rice has been the primary staple food [10]. Shocks in rice production have a vast possibility impact to generate problems in the economy as a whole. It is necessary to hold rice prices at affordable levels. In early developing countries, rice price movements have a significant impact to change the number of people below the threshold of poverty [11]. Conversely, the role of agriculture to take a part in economic development such as poverty reduction start to decline once a region enters a developed economy [12]. To this day, Indonesia is still in the stage of developing economy; therefore, the agricultural sector performance is expected to have a remarkable impact to assist poverty eradication.

Numerous quantitative methods have been employed with the aim of investigating the linkage between paddy and poverty. For instance, Moses et al. [13] employed multi-stage sampling and logit models in order to examine the linkage between rice production and poverty in Nigeria. The results found that annual income from rice production has a significant impact on poverty reduction. In another study, Rajindra et al. [14] noted that the amount of rice production affected farmers' income and feasibility index in Labuan Taposo village, Donggala. Enhancing rice productivity is a key strategy to spur poverty reduction [14]. Similarly, Arouna et al [15] performed a metadata analysis and found that improving rice varieties has a notable role in achieving food security and declining poverty rates in Sub-Sahara Africa.

Moving to broader agricultural proxies, Bekun & Akadiri [16] examined the causal connection between Agriculture Value Added (AVA) and poverty rates using a panel of nine Southern Africa Countries. Second-generation panel methods, i.e., Cross-sectionally augmented IPS (CIPS) unit root, Westerlund and Edgerton cointegration, and Dumitrescu-Hurlin (DH) causality methods, were applied. Empirical findings found that cointegration among variables is evident and there was a bidirectional causality between AVA and poverty reduction. Nonetheless, a time-series study by Tochukwu et al. [17] noted that a two-way causal connection between AVA and poverty in Nigeria was not evident. Conversely, there is a one-way causality from poverty to AVA. Also, there is unidirectional causal nexus from Food Production Index (FPI) to poverty reduction. Furthermore, Matthew et al. [18] employed a General Method of Moments (GMM) and found that AVA has a positive impact on poverty reduction.

Against this background, this study intends to examine the causal linkage between paddy productivity and poverty in Sumatra. To the best author's knowledge, an empirical analysis on this angle is still neglected.

Previous studies in the case of Indonesia context focus on the causal connection between economic growth and poverty rates [19][20][21][22]. The reasons and contributions of this empirical research are as follows. This paper chooses a specific case of provinces on Sumatra Island. Previous studies on this angle commonly focus on the aggregate data of Indonesia or Java Island. Further, this article applies econometric methods that accommodate heterogeneity panels. The Pesaran-Yamagata and Blomquist-Westerlund tests are applied in order to check homogeneity slopes. Following the homogeneity test, this paper employs the Dumitresu-Hurlin (DH) causality and Pooled Mean Group (PMG) with the aim of unraveling the causal linkage between paddy productivity and poverty rates in Sumatra.

2. RESEARCH METHODS

This research employs balanced panel data and dynamic heterogeneous methods with the aim of testing the causal linkage between paddy and poverty in the case of Sumatra. The data, variables, and estimation methods applied are as follows:

2.1 Data

Balanced panel data comprising ten provinces in Sumatra for the period 2010-2020 are utilized in this analysis. Those provinces are Sumatera Utara, Sumatera Barat, Bengkulu, Lampung, Riau, Jambi, Kepulauan Bangka Belitung, Kepulauan Riau, Aceh, and Sumatera Selatan. There are two variables used in this research, namely poverty rates and paddy productivity. A Head Count Index (HCI-P0) is applied as a proxy for poverty rates. This figure refers to the percentage of people below the poverty line. Paddy productivity is measured by lowland rice production produced by one hectare of land. All datasets used are retrieved from the Central Bureau of Statistics (BPS). The number of observations is 130 individuals (n), consisting of 10 series (T) and 13 cross-sections (N), which is appropriate for numerous econometrics methods.

2.2 Homogeneity Slope Test

It is meaningful to check for slope heterogeneity prior to performing any panel estimation techniques. This idea comes up because several methods such as Levin-Lin-Chu (LLC), Kao residual test, and traditional Granger causality test assume slope homogeneity. Those approaches are no longer proper to be applied if the assumption of homogeneity fails to be fulfilled. Hence, this paper employs a procedure developed by Pesaran & Yamagata [23] (P-Y test). The P-Y test is proper to be enforced in cases of long panel, i.e., $T > N$. Also, this technique accommodates the issue of cross-sectional dependence. Equations for the slope homogeneity test can be written as follows [24][25]:

$$\tilde{\Delta}_{SH}= (N)^{\frac{1}{2}}(2k)^{-\frac{1}{2}}\left(\frac{1}{N}\tilde{S}-k\right) \tag{1}$$

and

$$\tilde{\Delta}_{ASH} = (N)^{\frac{1}{2}}\left(\frac{2k(T-K-1)}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\tilde{S}-k\right) \tag{2}$$

where Equation (1) and Equation (2) produce the delta tilde ($\tilde{\Delta}_{SH}$) and the adjusted delta tilde ($\tilde{\Delta}_{ASH}$), respectively; k is the number of exogenous regressors; $\tilde{S}$ stands for Swammy's test statistic; N refers to cross-dimension. The null hypothesis of slope homogeneity is proposed. This paper checks the H_0 on the p-value at a 5% level. For the robustness check, this research considers a technique developed by Blomquist & Westerlund [26] (B-W test). This approach has the ability to identify slope homogeneity under the condition of serial correlation and heteroscedasticity problems.

2.3 Panel Unit Root Test

It is requisite to check the integrated order of research variables prior to the empirical estimation. The DH causality test and PMG method are no longer proper to be applied if there is any variable that is stationary at the second difference. This paper employs the IPS and Fisher-ADF tests since both methods are appropriate to use under the dynamic heterogeneity panels [27]. The IPS test is derived from the mean of individual unit root statistics. Alternatively, the Fisher-ADF adopts the Fisher procedure to examine test that integrate the p-value from individual tests [28]. A formal model for the stationary test can be specified as follow:

$$\Delta y_{it} = \alpha_i + \nu_i t + \beta_i y_{it-1} + \sum_{k=1}^{n} \phi_i y_{it-k} + \varepsilon_{it} \quad (3)$$

where y is the research variable across provinces over period t; Δ is the first difference operator; k shows the number of lags specified for the ADF equation; ρ_i is an autoregressive coefficient; ε is the error term supposed to be $\sim N(0,1)$. The null hypothesis of the non-stationary series (there is a unit root) is proposed in both IPS and Fisher-type tests, that is, $H_0: \beta_i = 0, \forall i$, against the alternative, $H_0: \beta_i < 1$. The parameter of β_i is allowed to vary across provinces in order to represent heterogeneous panels. The fisher-ADF test can be estimated by following **Equation (4)** and **Equation (5)** **[29]**:

$$ADF - \text{fisher } I = -2 \sum_{n=1}^{N} \log(pi) \to \chi^2_{2N} \quad (4)$$

$$ADF - \text{Choi } Z = \frac{1}{\sqrt{N_{n=1}}} \sum_{n-1}^{N} \phi^{-1}(pi) \to N(0,1) \quad (5)$$

pi shows the p-value from the ADF equation for individual n. ϕ^{-1} depicts the inverse of the standard normal Cumulative Distribution Function (CDF).

2.4 Panel Cointegration Test

The presence of long-term nexus between variables can be examined by the cointegration test. Hence, this paper employs methods proposed by Pedroni **[30]** which can be applied both in the case of homogeneity or heterogeneity panels. The common AR (group statistics) is derived from the average results of individual test statistics whilst the individual AR (panel statistics) pools the statistics along the within-dimension **[31]**. Group and panel statistics in the Pedroni test adopt residual-based tests. **Equation (6)** – **Equation (9)** show general models to test cointegration **[31]**:

$$y_{it} = v_i + \gamma_{1i} x_{1it} + \gamma_{2i} x_{2it} + \cdots + \gamma_n x_{Mit} + e_{i,t} \quad (6)$$

$$\Delta y_{it} = \sum_{m=1}^{M} \gamma_{mi} \Delta x_{mit} + u_{it} \quad (7)$$

$$\hat{e}_{it} = \hat{\pi}_i \hat{e}_{it-1} + \hat{\varepsilon}_{it} \quad (8)$$

$$\hat{e}_{it} = \hat{\pi}_i \hat{e}_{it-1} \sum_{k=1}^{K} \hat{\pi}_k \Delta \hat{e}_{it-k} + \hat{\varepsilon}^*_{it} \quad (9)$$

where $t = 1,2, \ldots T$ is the number of series; $i = 1,2 \ldots N$ is the number of individuals in the pooled data. $m = 1,2, \ldots M$ shows the number of explanatory variables; γ denotes the slope coefficient; v and e are the intercept and error terms, respectively. $\hat{e}$ is the estimated error term.

2.5 Dumitrescu-Hurlin Causality Test

This paper employs a causality method proposed by Dumitrescu & Hurlin **[32]**. DH causality test can be applied both in short panel ($N > T$) and long panel ($N < T$) and is more robust and proper as compared to the previous procedure, i.e., Granger non-causality test **[33]**. Furthermore, this method has the ability to address some critical issues in pooled data such as individual heterogeneity and cross-sectional dependence. Previous studies have utilized this method **[33]** **[34]** **[35]**. A general model can be written as follow:

$$y_{it} = \eta_i + \sum_{k=1}^{k} \pi_1 y_{i,t-k} + \sum_{k=1}^{k} \lambda_i x_{i,t-k} + u_{i,t} \quad (10)$$

where y_{it} and x_{it} are the stationary variables and they are cointegrated. t and i express period (T) and cross-section (N), respectively. k shows the lag order and it is supposed to be the same for all individuals. The $\alpha_i^{(p)}$

and $\beta_i^{(p)}$ signify the autoregressive and explanatory parameters. The null and alternative hypotheses of the DH causality test are:

$H_0: \lambda_i = 0, \forall_i = 1, \dots N$

$H_1: \lambda_i \neq 0, \forall_i = N+1, N+2 \dots N$

For the hypothesis test, the DH causality method utilizes the average Wald ($\overline{W}$) statistics and tests the H_0 by estimating the z-bar ($\bar{z}$) or z-bar tilde ($\tilde{z}$) statistics [36].

2.6 Pooled Mean Group

Last, of all, this study applies the PMG (or Panel-ARDL) developed by Pesaran et al. [37] with the aim of estimating the elasticity. Panel-ARDL is appropriate for heterogeneity panels because it permits the short-run coefficients and speeds of adjustment to be varied across individuals [38]. Homogeneity restriction only holds for long-run parameters. This method is proper for this study given that it performs better as compared to the GMM method in the case of $T > N$. Moreover, Panel-ARDL offers consistent and efficient estimators given that it reduces the issues emerging from endogeneity by plugging sufficient lag for both regressand and regressor [39]. The PMG (p q) model can be specified as follow [37][40]:

$$\ln POV_{it} = \sum_{j=0}^{p} \delta'_{ij} \ln POV_{it-j} + \sum_{j=0}^{p} \vartheta'_{ij} \ln PPD_{it-j} + v_i + \varepsilon_{it} \tag{11}$$

By re-parameterization, **Equation (7)** can be modified as follow:

$$\Delta POV_{it} = \phi_i \ln POV_{it-1} + \beta_i \ln PPD_{it} + \sum_{j=0}^{p} \delta'_{ij} \ln POV_{it-j} + \sum_{j=0}^{p} \vartheta'_{ij} \ln PPD_{it-j} + v_i + \varepsilon_{it} \tag{12}$$

where:

$$\phi_i = -1\left(1 - \sum_{j=1}^{p} \delta'_{ij}\right)$$

$$\beta_i = \sum_{j=0}^{p} \vartheta'_{ij}$$

$$\delta'_{ij} = -\sum_{m=j+1}^{p} \delta_{im}, \qquad j = 1,2,3 \dots p-1, and$$

$$\vartheta'_{ij} = -\sum_{m=j+1}^{q} \vartheta_{im}, \qquad j = 1,2,3, \dots q-1$$

By grouping variables in levels, a panel error correction equation is defined as follows:

$$\Delta \ln POV_{it} = \phi_i(\ln POV_{it-1} - \gamma_0 - \gamma'_i \ln PPD_{it}) + \sum_{j=1}^{p-1} \delta'_{ij} \Delta \ln POV_{it-j} + \sum_{j=0}^{p-1} \vartheta'_{ij} \Delta \ln PPD_{it-j} + v_i + \varepsilon_{it} \tag{13}$$

where δ_i and ϑ_i denote the short-run coefficients of the lags of poverty rates and paddy productivity. $\gamma_i = -(\beta_i/\phi_i)$ shows the long-run parameters. ψ_i denotes the parameter of error correction term which is critical to check the existence of long-run equilibrium. For confirmation, the ECM_{t-1} parameter of ψ_i must be a negative value $(-1 < \psi_i < 0)$ and be statistically significant. ψ_i depicts the speed of adjustment respecting long-term equilibrium. Finally, the estimates of parameters are calculated by:

$$\hat{\gamma}_{PMG} = \frac{\sum_{i=1}^{N} \tilde{\gamma}}{N}; \ \hat{\delta}_{PMG} = \frac{\sum_{i=1}^{N} \tilde{\delta}}{N}; \ and \ \hat{\vartheta}_{PMG} = \frac{\sum_{i=1}^{N} \tilde{\vartheta}}{N}$$

where $j = 0, \dots q-1$, and $\hat{\phi}_{PMG} = \tilde{\phi}$

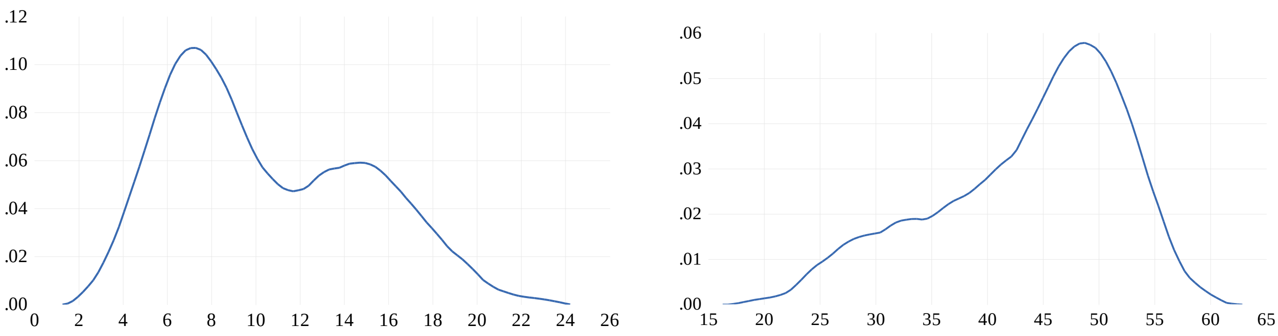
3. RESULTS AND DISCUSSION

To commence with the discussion, descriptive statistics of research variables are displayed in Table 1. During the period of analysis (2010 – 2022), the mean value of poverty rates is 10.49% and it ranges from 4.50% to 20.98%. Paddy productivity has a mean value of 43.77 tons and it is around 22.85 to 56.49 tons. All variables used are not normally distributed since the J-B test results denote that the Chi2 statistics are less than the Chi2 table (42.56). Thus, they are platykurtic distributed. Additionally, Figure 1 displays the kernel density function of paddy productivity (a) and poverty rates (b).

Table 1. Descriptive Statistics

	Mean	Med	Max	Min	Std. Dev.	JB
POV	10.49	8.94	20.98	4.50	4.28	10.34
PPD	43.77	46.00	56.49	22.85	8.09	12.79

Note: JB test uses a 5% significance level.



(a) (b)

Figure 1. The kernel density graph of poverty rates (a) and paddy productivity (b)

Table 2 presents the outcomes of the slope homogeneity test. The P-Y test denotes that the H_0 of slope homogeneity cannot be accepted. Similarly, the alternative technique of the B-W test is found to be rejected the H_0 at a 1% significance level. These findings imply the presence of slope heterogeneity across provinces in Sumatra. Hence, concerning methods that cover slope heterogeneity are requisite.

Table 2. Slope Homogeneity Test Results

	Pesaran-Yamagata		Blomquist-Westerlund	
	Delta	p-value	Delta	p-value
	4.572***	0.000	3.366***	0.001
adj.	5.213***	0.000	3.838***	0.000

Note: *** denotes significance at a 1% level

Following the slope homogeneity test results, both IPS and Fisher-type are proper methods to test the presence of unit roots. Table 2 presents the outcomes. The results denote that POV is stationary at the level, while PPD is non-stationary. Nonetheless, PPD is found to be stationary after taking the first difference. The IPS and Fisher-ADF tests point out that the order of integration is mixed, i.e., $I(0)$ and $I(1)$. Thus, the PMG estimation is appropriate to be applied since none of the variables is found to be $I(2)$.

Table 3. Unit Root Test Results

Deterministic =		Intercept		Intercept & trend	
		level	1st difference	level	1st difference
IPS	POV	-2.73449***	-8.53147***	-2.00103	-6.94783***
		(0.0031)	(0.0000)	(0.0227)	(0.0000)
	PPD	0.30710	-5.57115***	-0.23426	-3.55072***
		(0.6206)	(0.0000)	(0.4074)	(0.0002)

Deterministic =		Intercept		Intercept & trend	
		level	1st difference	level	1st difference
Fisher-ADF	POV	43.0063***	94.0388***	32.6534***	77.4998***
		(0.0020)	(0.0000)	(0.0368)	(0.0000)
	PPD	18.4928	65.1138***	22.9526	47.9694***
		(0.5550)	(0.0000)	(0.2911)	(0.0004)

Note: the lag length was automatically selected by the AIC method. P-values are in the parentheses. *** indicates significance at a 1% level.

The outcomes of cointegration tests are displayed in **Table 3**. Following the presence of heterogeneity among provinces, Pedroni with individuals AR (within dimension) method is more appropriate to be applied compared to common AR because it covers heterogeneous slope, intercept, and trend. The results of Group PP and ADF statistics denote that the null hypothesis of no level relationship is found to be rejected at a 1% significance level. Given those findings, there is a long-run heterogeneous connection between poverty rates and paddy productivity in Sumatra.

Table 4. Cointegration Test Results

	Within-dimension (Common AR)		Between-dimension (Individual AR)	
	Statistic	p-value	Statistic	p-value
Panel v-Statistic	3.36301***	0.0004		
Panel/Group rho-Statistic	0.08178	0.5326	0.78425	0.7836
Panel/Group PP-Statistic	-3.78438***	0.0001	-5.01417***	0.0000
Panel/Group ADF-Statistic	-3.28148***	0.0005	-4.33122***	0.0000

Note: the automatic lag length was selected by the SC method. *** denotes significance at a 1% level

Since the cointegration relationship is evident, it is meaningful to reveal the causal nexus between the variables investigated. Causality analysis has an essential function in order to promote policy direction. The DH-causality test results are presented in **Table 4**. In regard to Z-bar tilde statistics, the results cannot reject the H_0 that POV does not cause PPD; however, the H_0 that PPD does not cause POV is found to be declined at a 1% significance level. Thus, there is a unidirectional causal linkage that flows from paddy productivity toward poverty rates in Sumatra.

Table 5. Pairwise DH-Causality Test Results

H_0: x_{it} does not homogeneously cause y_{it}	W-bar stats.	Z-bar stats.	Z-bar tilde
PPD → POV	10.5839	13.5723***	3.0761***
		(0.0000)	(0.0021)
POV → PPD	5.4379	5.4358***	0.8929
		(0.0000)	(0.3719)

Note: the lag length (2) was selected by the VAR-SC method. *** denotes significance at a 1% level. The H_0 is tested based on the Z-bar tilde statistics

The DH causality results point out that a change in paddy productivity causes a change in poverty rates. Nonetheless, a change in poverty rates has no significant impact on paddy productivity. Consequently, these results imply that it is pivotal to enhance (or at least maintain) paddy productivity. Shocks in paddy sectors can be transmitted to poverty rates. In other words, the number of people below the national poverty line is dependent on the rice sector's performance. Also, this implies that the number of vulnerable households with regard to food security is significant. These empirical findings can be both a negative and positive signal for policymakers. Poverty rates in Sumatra are conditional on paddy productivity.

The PMG procedure is applied in order to estimate the elasticity of paddy productivity with respect to poverty rates. It is used because it has the advantage to estimate the short- and long-run coefficients. Also, this method accommodates non-stationary data and heterogeneity among individual panels. Given the optimal lags of 2 and the automatic lag structure selection by the SC method, the PMG (1,1), i.e., $p = 1$ and $q = 1$, is the most appropriate model.

Table 6. **PMG, FMOLS, and DOLS Estimation Results**

	PMG	FMOLS	DOLS
	Long run equation		
Ln (PPD)	-0.482202***	-0.55827***	-0.52903***
	(0.107009)	(0.147123)	(0.186591)
	Short run equation		
ECM (-1)	-0.366335***		
	(0.069798)		
ΔLn (PPD)	0.292353**		
	(0.139645)		
Constant	1.473204***		
	(0.312940)		
R-squared		0.954560	0.985167

Note: standard errors are in the parentheses; *** denotes significance at a 1% level

The short- and long-run models of PMG estimation are presented in **Table 6**. The ECM coefficient is found to be negative (-0.366) and statistically significant at a 5% level. This result denotes that short-term shock in the economy will be adjusted around 0.37% within a year to bounce back to the long-run equilibrium. Surprisingly, paddy productivity has a positive impact on poverty rates at a 5% significance level in the short run. This result implies that paddy commodities cannot be used as an instrument for poverty alleviation in the short run. However, paddy productivity has a negative impact on poverty rates at a 1% significance level in the long run. An increase in 1% paddy productivity has a beneficial impact on to decline of approximately 0.48% poverty rates in Sumatra, ceteris paribus.

For the robustness check, this paper utilizes cointegrated regressions. As shown in **Table 6**, the long-run parameters of PMG are consistent with the alternative methods which are FMOLS and DOLS. It can be stated that the negative nexus between paddy productivity and poverty rates in Sumatra is robust. Thus, paddy is a strategic commodity with the aim of poverty alleviation. This finding is consistent with previous studies in India, Sub Sahara Africa, Nigeria, and Indonesia **[15][14][13][41]**. Augmenting paddy productivity has a pivotal role to generate technical efficiency. Further, sufficient paddy production is necessary for the reason of holding affordable rice prices for consumers who are poor. Once the paddy sector fails to meet its domestic demand; consequently, it would rapidly cause an increase in rice prices, reduce consumers' real income, and in turn, boost the number of people below the poverty line.

4. CONCLUSIONS

The current paper aims to estimate the causal linkage between paddy productivity and poverty rates in Sumatra for the period 2010-2022 by employing dynamic heterogeneity panel methods. Several key findings can be drawn as follows:

1. The P-Y and B-W tests validate there is heterogeneity among provinces in Sumatra; consequently, it is requisite to adopt methods that accommodate slope heterogeneity.
2. All the variables used are mixed order of integration and they are cointegrated; hence, the DH causality and PMG estimation methods are appropriate to be applied.
3. There is a unidirectional causal nexus that flow from paddy productivity toward poverty rates. Thus, a change in paddy productivity causes a change in poverty rates. Following the long-run PMG estimation results, a 1% increase in paddy productivity has a beneficial role to decline around 0.48% poverty rates.
4. The long-run estimated parameters of PMG are robust given that they are consistent with the alternative methods such as FMOLS and DOLS.

REFERENCES

[1] Z. A. Abro, B. A. Alemu, and M. A. Hanjra, "Policies for Agricultural Productivity Growth and Poverty Reduction in Rural Ethiopia," *World Dev.*, vol. 59, pp. 461–474, 2014, doi: https://doi.org/10.1016/j.worlddev.2014.01.033.

[2] Almwd Hafi, "Agricultural Production and Economic Growth in Nigeria: Implication for Rural Poverty Alleviation," *Q. J. Int. Agric.*, vol. 53, no. 3, pp. 207–223, 2014, doi: 10.22004/ag.econ.195735.

[3] S. Muthayya, J. D. Sugimoto, S. Montgomery, and G. F. Maberly, "An overview of global rice production, supply, trade, and consumption," *Ann. N. Y. Acad. Sci.*, vol. 1324, no. 1, pp. 7–14, Sep. 2014, doi: https://doi.org/10.1111/nyas.12540.

[4] R. Prasad, Y. S. Shivay, and D. Kumar, "Current Status, Challenges, and Opportunities in Rice Production BT - Rice Production Worldwide," B. S. Chauhan, K. Jabran, and G. Mahajan, Eds., Cham: Springer International Publishing, 2017, pp. 1–32. doi: 10.1007/978-3-319-47516-5_1.

[5] R. B. R. Firdaus, M. Leong Tan, S. R. Rahmat, and M. Senevi Gunaratne, "Paddy, rice and food security in Malaysia: A review of climate change impacts," *Cogent Soc. Sci.*, vol. 6, no. 1, p. 1818373, Jan. 2020, doi: 10.1080/23311886.2020.1818373.

[6] L. Christiaensen and W. Martin, "Agriculture, structural transformation and poverty reduction: Eight new insights," *World Dev.*, vol. 109, pp. 413–416, 2018, doi: https://doi.org/10.1016/j.worlddev.2018.05.027.

[7] A. Dhrifi, "Agricultural Productivity and Poverty Alleviation: What Role for Technological Innovation," *J. Econ. Soc. Stud.*, vol. 4, no. 1, pp. 131–151, 2014, doi: 10.14706/jecoss11418.

[8] M. R. Aprillya, E. Suryani, and A. Dzulkarnain, "System Dynamics Simulation Model to Increase Paddy Production for Food Security," *J. Inf. Syst. Eng. Bus. Intell.*, vol. 5, no. 1, p. 67, 2019, doi: 10.20473/jisebi.5.1.67-75.

[9] P. S. Dalton, V. H. G. Jimenez, and C. N. Noussair, "Exposure to poverty and productivity," *PLoS One*, vol. 12, no. 1, pp. 1–19, 2017, doi: 10.1371/journal.pone.0170231.

[10] J. Mariyono, "Rice production in Indonesia : policy and performance," *Asia Pacific J. Public Adm.*, vol. 36, no. 2, pp. 123–134, 2014, doi: 10.1080/23276665.2014.911489.

[11] S. W. Deski, S. Sartiyah, and C. Seftarita, "Investigating the Effect of Rice Commodity Price Volatility on Provincial Capital Poverty: An Evidence from Indonesia," *Int. J. Glob. Optim. Its Appl.*, vol. 1, no. 2, pp. 90–99, 2022, doi: 10.56225/ijgoia.v1i2.18.

[12] M. Ivanic and W. Martin, "Sectoral Productivity Growth and Poverty Reduction: National and Global Impacts," *World Dev.*, vol. 109, pp. 429–439, 2018, doi: 10.1016/j.worlddev.2017.07.004.

[13] O. O. Moses, E. J. Ongbele, and I. T. Rhoda, "ice Production and Poverty Reduction in Agatu Local Government Area of Benue State, Nigeria." pp. 1–8, 2019. doi: 10.9734/ajaar/2019/v10i430037.

[14] Rajindra, S. Jumiyati, and Irmawati, "Increasing production and income of rice farming: Keywords of food security and poverty alleviation," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 870, no. 1, 2021, doi: 10.1088/1755-1315/870/1/012021.

[15] A. Arouna, J. C. Lokossou, M. C. S. Wopereis, S. Bruce-Oliver, and H. Roy-Macauley, "Contribution of improved rice varieties to poverty reduction and food security in sub-Saharan Africa," *Glob. Food Sec.*, vol. 14, no. March, pp. 54–60, 2017, doi: 10.1016/j.gfs.2017.03.001.

[16] F. Victor Bekun and S. Saint Akadiri, "Poverty and Agriculture in Southern Africa Revisited: A Panel Causality Perspective," *SAGE Open*, vol. 9, no. 1, 2019, doi: 10.1177/2158244019828853.

[17] O. R. Tochukwu, W. D. Olanipekun, O. S. Omoyele, and T. A. Aderemi, "Agriculture, Food Security and Poverty Reduction in Nigeria: Cointegration and Granger Causality Approach," *Acta Univ. …*, vol. 18, no. 1, pp. 126–135, 2022, [Online]. Available: https://dj.univ-danubius.ro/index.php/AUDOE/article/view/1568

[18] O. A. Matthew, R. Osabohien, T. O. Ogunlusi, and O. Edafe, "Agriculture and social protection for poverty reduction in ECOWAS," *Cogent Arts Humanit.*, vol. 6, no. 1, 2019, doi: 10.1080/23311983.2019.1682107.

[19] A. Erlando, F. D. Riyanto, and S. Masakazu, "Financial inclusion, economic growth, and poverty alleviation: evidence from eastern Indonesia," *Heliyon*, vol. 6, no. 10, p. e05235, 2020, doi: 10.1016/j.heliyon.2020.e05235.

[20] L. Nansadiqa, R. Masbar, and M. S. A. Majid, "EASJEBM_22_46-52_c_rkW2Udi," *East African Sch. J. Econ. Bus. Manag.*, vol. 2, no. 2, pp. 46–51, 2019, doi: 10.36349/easjebm.2019.v02i0.

[21] Akhmad and N. S. Marsuni, "Causality Relationship of Poverty , Unemployment Rate , and Economic Growth in South Sulawesi," *J. Ekon. Balanc.*, vol. 15, pp. 231–241, 2019, [Online]. Available: https://journal.unismuh.ac.id/index.php/jeb/article/view/3505

[22] D. D. P. Sari, S. Sukanto, T. Marwa, and A. Bashir, "The Causality between Economic Growth, Poverty, and Stunting: Empirical evidence from Indonesia," *J. Perspekt. Pembiayaan dan Pembang. Drh.*, vol. 8, no. 1, pp. 13–30, 2020, doi: 10.22437/ppd.v8i1.8834.

[23] M. H. Pesaran and T. Yamagata, "Testing slope homogeneity in large panels," *J. Econom.*, vol. 142, no. 1, pp. 50–93, 2008, doi: 10.1016/j.jeconom.2007.05.010.

[24] Z. Khan, S. Ali, M. Umar, D. Kirikkaleli, and Z. Jiao, "Consumption-based carbon emissions and International trade in G7 countries: The role of Environmental innovation and Renewable energy," *Sci. Total Environ.*, vol. 730, p. 138945, 2020, doi: 10.1016/j.scitotenv.2020.138945.

[25] A. Safi, Y. Chen, S. Wahab, S. Ali, X. Yi, and M. Imran, "Financial Instability and Consumption-based Carbon Emission in E-7 Countries: The Role of Trade and Economic Growth," *Sustain. Prod. Consum.*, vol. 27, pp. 383–391, 2021, doi: 10.1016/j.spc.2020.10.034.

[26] J. Blomquist and J. Westerlund, "Testing slope homogeneity in large panels with serial correlation," *Econ. Lett.*, vol. 121, no. 3, pp. 374–378, 2013, doi: 10.1016/j.econlet.2013.09.012.

[27] K. S. Im, M. H. Pesaran, and Y. Shin, "Testing for unit roots in heterogeneous panels," *J. Econom.*, vol. 115, no. 1, pp. 53–74, 2003, doi: 10.1016/S0304-4076(03)00092-7.

[28] U. Al-Mulali, C. F. Tang, and I. Ozturk, "Estimating the Environment Kuznets Curve hypothesis: Evidence from Latin America and the Caribbean countries," *Renew. Sustain. Energy Rev.*, vol. 50, pp. 918–924, 2015, doi: 10.1016/j.rser.2015.05.017.

[29] K. Dong, R. Sun, G. Hochman, X. Zeng, H. Li, and H. Jiang, "Impact of natural gas consumption on CO2 emissions: Panel

data evidence from China's provinces," *J. Clean. Prod.*, vol. 162, pp. 400–410, 2017, doi: 10.1016/j.jclepro.2017.06.100.
[30] P. Pedroni, "Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis," *Econom. Theory*, vol. 20, no. 3, pp. 597–625, 2004, doi: 10.1017/S0266466604203073.
[31] T. Neal, "Panel cointegration analysis with xtpedroni," *Stata J.*, vol. 14, no. 3, pp. 684–692, 2014, doi: 10.1177/1536867x1401400312.
[32] E. I. Dumitrescu and C. Hurlin, "Testing for Granger non-causality in heterogeneous panels," *Econ. Model.*, vol. 29, no. 4, pp. 1450–1460, 2012, doi: 10.1016/j.econmod.2012.02.014.
[33] S. H. Hashmi, H. Fan, Y. Habib, and A. Riaz, "Non-linear relationship between urbanization paths and CO2 emissions: A case of South, South-East and East Asian economies," *Urban Clim.*, vol. 37, no. February, p. 100814, 2021, doi: 10.1016/j.uclim.2021.100814.
[34] M. E. Destiartono and D. Hartono, "Does Rapid Urbanization Drive Deforestation ? Evidence From Southeast Asia," *Econ. Dev. Anal. J.*, vol. 11, no. 4, pp. 442–453, 2022, [Online]. Available: https://journal.unnes.ac.id/sju/index.php/edaj/article/view/58870
[35] B. A. Ajanaku and A. R. Collins, "Economic growth and deforestation in African countries: Is the environmental Kuznets curve hypothesis applicable?," *For. Policy Econ.*, vol. 129, p. 102488, 2021, doi: 10.1016/j.forpol.2021.102488.
[36] L. Lopez and S. Weber, "Testing for Granger causality in panel data," *Stata J.*, vol. 17, no. 4, pp. 972–984, 2017, doi: 10.1177/1536867X1801700412.
[37] M. H. Pesaran, Y. Shin, R. P. Smith, and M. Hashem, "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels," *Source J. Am. Stat. Assoc.*, vol. 94, no. 446, pp. 621–634, 1999, Accessed: Jun. 10, 2022. [Online]. Available: https://doi.org/10.2307/2670182
[38] M. A. Malik and T. Masood, "Dynamics of Output Growth and Convergence in the Middle East and North African Countries: Heterogeneous Panel ARDL Approach," *J. Knowl. Econ.*, vol. 13, no. 2, pp. 1444–1469, 2022, doi: 10.1007/s13132-021-00780-3.
[39] I. Attiaoui, H. Toumi, B. Ammouri, and I. Gargouri, "Causality links among renewable energy consumption, CO2 emissions, and economic growth in Africa: evidence from a panel ARDL-PMG approach," *Environ. Sci. Pollut. Res.*, vol. 24, no. 14, pp. 13036–13048, 2017, doi: 10.1007/s11356-017-8850-7.
[40] K. Sohag, A. B. Nabilah, and R. A. Begum, "Dynamic impact of financial development on economic growth: Heterogeneous panel data analysis of island economies," *Int. J. Econ. Policy Emerg. Econ.*, vol. 8, no. 1, pp. 77–95, 2015, doi: 10.1504/IJEPEE.2015.068249.
[41] D. R. Safitri and E. D. Sihaloho, "Lumbung Padi Indonesia dan Kemiskinan : Studi Kasus Kabupaten Kota di Jawa Timur," *Ekon. J. Econ. Bus.*, vol. 4, no. September 2018, pp. 56–61, 2020, doi: 10.33087/ekonomis.v4i1.109.