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Indonesian Economy Under the Shadow of Catastrophic Natural Disasters: Empirical Evidences from Additive Mixed Model With P-Spline Smooth Function

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ABSTRACT

As located within the Ring of Fire with more than half of the volcanoes are active making Indonesia as one of the most vulnerable countries to natural disasters. Moreover, Indonesia was ranked 12th of 35 countries with the highest risk from natural disasters by the World Bank in 2021. Such multiple disasters could hamper the Indonesian economy through disaster loss. This study is conducted to investigate the impact of several natural disasters, including hydrological, meteorological, climatological, and geophysical, on Indonesian economic growth of 34 provinces in Indonesia from 2018 to 2022 represented by annual per capita real output growth. While the disaster damages are measured by the number of affected people and the number of damaged infrastructures. The econometric approach of panel data analysis is employed and further extended to the additive mixed model with P-spline smooth function to capture the non-linear relationship. The human development index (HDI) and financial realization of the unexpected budget are also incorporated in the models. The results show that the best model, the P-spline model, could capture the nature of the non-linear relationship between natural disasters and economic growth. In addition, the estimation process is also carried out separately for each group based on the HDI and financial ability. The variation of impact behaviour from natural disasters is clearly revealed by modelling each group based on HDI and financial ability indicating that each provincial group has a different impact transmitted by the natural disasters.

1. INTRODUCTION

As located in the Ring of Fire with more than half of the volcanoes are active and in the junction of the three giant plates of Pacific, Eurasia, and Indo-Australia make Indonesia as one of the most vulnerable countries to natural disasters (Wibowo et al., 2022; Wibowo, Purwa, et al., 2021; Wibowo, Ulama, et al., 2021). Indonesia was ranked 12th of 35 countries with the highest risk from natural disasters (World Bank,

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2021). In addition, based on the World Risk Report 2019, Indonesia was ranked 37th as the most vulnerable country to disasters among the 180 countries (Ministry of Finance Republic of Indonesia, 2020). As experienced several catastrophic natural disasters in the last few years, the level of disaster's vulnerable is getting worse hence making Indonesia as the third country with the most vulnerable to disaster worldwide in 2022 (Atwii et al., 2022). Such multiple disasters could hamper the Indonesian economy and government finance through disaster loss by the number of people affected and damage of infrastructures. As reported by the Indonesian Ministry of National Development Planning-Bappenas (2021), the economic potential loss of natural disasters caused by the climate change for four priority sectors, i.e. marine and coastal, water, agriculture, and health, was projected around 102 to 115 trillion Rupiahs during 2020-2024. For a comparison, the projected economic potential loss was about 0.56 percent of Indonesian Gross Domestic Product (GDP) in 2022.

Some of the previous studies have discussed about the impact of natural disasters on the economic aspect with most of them utilized the country-level panel data for several periods and employed regression-based method, either panel regression or dynamic panel regression, e.g. Cavallo et al. (2021), Shabnam (2014), Skidmore and Toya (2002), Panwar and Sen (2019), and Loayza and Olaberri (2012). Rather than estimated the mean impact of natural disasters on economic growth, Bayoumi et al. (2021) performed quantile regression to estimate the impact of natural disasters on specific quantiles of economic growth. The results showed that there remains an inconclusive impact of natural disasters on the economy, either negative, no, or positive impact. Note that these studies only examined the linear impact of natural disasters on the economic growth. While, the non-linear relationship between the two macro indicators has never been explored before.

In addition, all of the previous studies stated before were focused on the country-level impact analysis. Motivated by these two conditions, this study investigates the impact of natural disasters, through the number of affected people and damaged infrastructure, on the provincial economic growth of Indonesia by performing the estimation of linear and non-linear models. The utilization of a non-linear model is expected to reveal the more flexible relationship between natural disasters and economic growth. To the best of our knowledge, there is still no study in Indonesia that discusses the impact of natural disasters, both generally and by each type or classification of natural disasters. Moreover, the estimation process is also performed separately for each of the provincial groups based on the Human Development Index (HDI) level and realization of financial for disaster management emergency response as a proxy for the financial ability when facing natural disasters. The results of this study are expected to provide some meaningful insights for the Indonesian government in terms of impact mitigation and disaster risk reduction to get resilient economic growth.

2. METHODOLOGY

2.1 Data and Variables

This study utilizes various annual data from different sources for the provincial level in Indonesia from 2018 to 2022. The per capita real output growth of 34 provinces in Indonesia, as a response variable, the Human Development Index (HDI), annual inflation, and unemployment rate, as control variables, are obtained from BPS-Statistics Indonesia (www.bps.go.id). The main explanatory variables, the number of affected people, including injured and dead, and the number of damaged infrastructures, including houses, economic, education, transportation facilities, etc., are obtained from Indonesian Disaster Information Data (DIBI) provided by National Agency for Disaster Management (BNPB) (dibi.bnpb.go.id). We also incorporate the disaster financial variable represented by the realization of the unexpected budget of disaster management emergency response obtained from the Ministry of Finance Republic of Indonesia (djpk.kemenkeu.go.id). As the time reference of this study contains the COVID-19 pandemic era, a dummy variable of COVID-19 is also incorporated in the model with 1 indicating COVID-19 condition from 2020

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to 2022 and 0 otherwise. Hence, we have balanced panel data of 34 provinces from 2018 to 2022 (170 observations).

2.2 Analytical Procedures

Several different strategies are performed to investigate the impact of natural disasters on Indonesian economic growth in this study with the analytical procedures are as follows:

1. Produce scatter plots for visually checking the relationship of each explanatory and response variable.
2. Estimate the impact of natural disasters by using the linear panel regression model, including the pooled cross sections or common effects model (CEM), fixed effects model (FEM), and random effects model (REM), and perform a model selection for panel regression including F-test, Lagrange Multiplier (LM) test, and Hausman test (Baltagi, 2005). The specification of CEM is as follows:

$$y_{it} = \alpha + X_{it}^T\beta + u_{it} \quad i = 1,2,\dots,N; t = 1,2,\dots,T \tag{1}$$

   with i and t denote province and year, respectively. This study only uses a one-way error component model specification $u_{it} = \mu_i + v_{it}$ with μ_i is time-invariant unobservable individual effect and v_{it} is error term, $v_{it} \overset{iid}{\sim} (0, \sigma_v^2)$. The unobservable individual effect μ_i is assumed as fixed parameter in FEM with specification as follows:

$$y_{it} = \alpha + \mu_i + X_{it}^T\beta + v_{it} \quad i = 1,2,\dots,N; t = 1,2,\dots,T \tag{2}$$

   While for REM, the μ_i is assumed as a random variable to overcome the degree of freedom lost in FEM, with $\mu_i \overset{iid}{\sim} (0, \sigma_\mu^2)$.
3. In the first strategy, we extend the previous linear panel regression model to a non-linear model by using the penalized spline or P-spline semiparametric panel regression. The penalized spline component is imposed in the linear model and represented as an additive random effect (Ruppert et al., 2003) making this model also called an additive mixed model (AMM). This model has been very popular for longitudinal or grouped data analysis (Harezlak et al., 2018) and semiparametric clustered data (Donnelly et al., 1995). The general specification of the additive mixed model used in this study is as follows:

$$y_{it} = \alpha + U_i + \beta_1 x + \sum_{k=1}^{K} \gamma_k (x - \kappa_k)_+ + v_{it} \quad i = 1,2,\dots,N; t = 1,2,\dots,T \tag{3}$$

   where U_i is random individual effect, $U_i \sim (0, \sigma_U^2)$, $\beta_1 x$ is fixed component, and $\sum_{k=1}^{K} \gamma_k (x - \kappa_k)_+$ is spline component with K is number of knots, γ_k is the k-th random effect of spline coefficient, $\gamma_k \sim (0, \sigma_\gamma^2)$, and $(x - \kappa_k)_+ = x - \kappa_k$ if $x > \kappa_k$ and 0 otherwise. Further, we evaluate the effective degrees of freedom (EDF) value of each explanatory variable to conclude the relation between each explanatory variable and a response variable, either linear or non-linear. The EDF value close to unity indicates linearity and a higher EDF value shows stronger a non-linearity relationship (Harezlak et al., 2018; Wilantari et al., 2022). We need to re-estimate the P-spline model when the linearity exists.
4. In the second strategy, we perform linear panel regression and P-spline panel regression models with two different specifications of natural disaster variables. First, we only utilize the total number of affected people and damaged infrastructures called Model-1. Second, we specify both variables by the type of natural disasters, including hydrological (flood and landslide), meteorological (cyclone), climatological (drought and forest fire), and geophysical (earthquake, tsunami, and

volcanic eruption), called Model-2, based on the general classification provided by the Centre for Research on the Epidemiology of Disasters (CRED).

5. Choose the best model between linear panel regression and P-spline models based on adjusted R-square.
6. Last, we apply the strategy from Asyahid and Pekerti (2022) that grouped the object of the study based on the HDI level and performed modeling for each group. The HDI is assumed to represent the quality of human capital and people's preparedness in a specific area when facing natural disasters since it consists of health, education, and economic dimensions (BPS-Statistics Indonesia, 2022b; UNDP, 2023). In addition, we improve the robustness of the estimation results by performing model estimation for each group of financial ability that is represented by the realization of the unexpected budget of disaster management emergency response. We have two groups based on HDI level, i.e. low-HDI (HDI<70) and high-HDI (HDI≥70), with the threshold value according to BPS-Statistics Indonesia (2022a). While for financial ability, we set the median value as a threshold for groping provinces into low-financial ability and high-financial ability. Hence, we obtained four groups based on the HDI and financial ability variables.

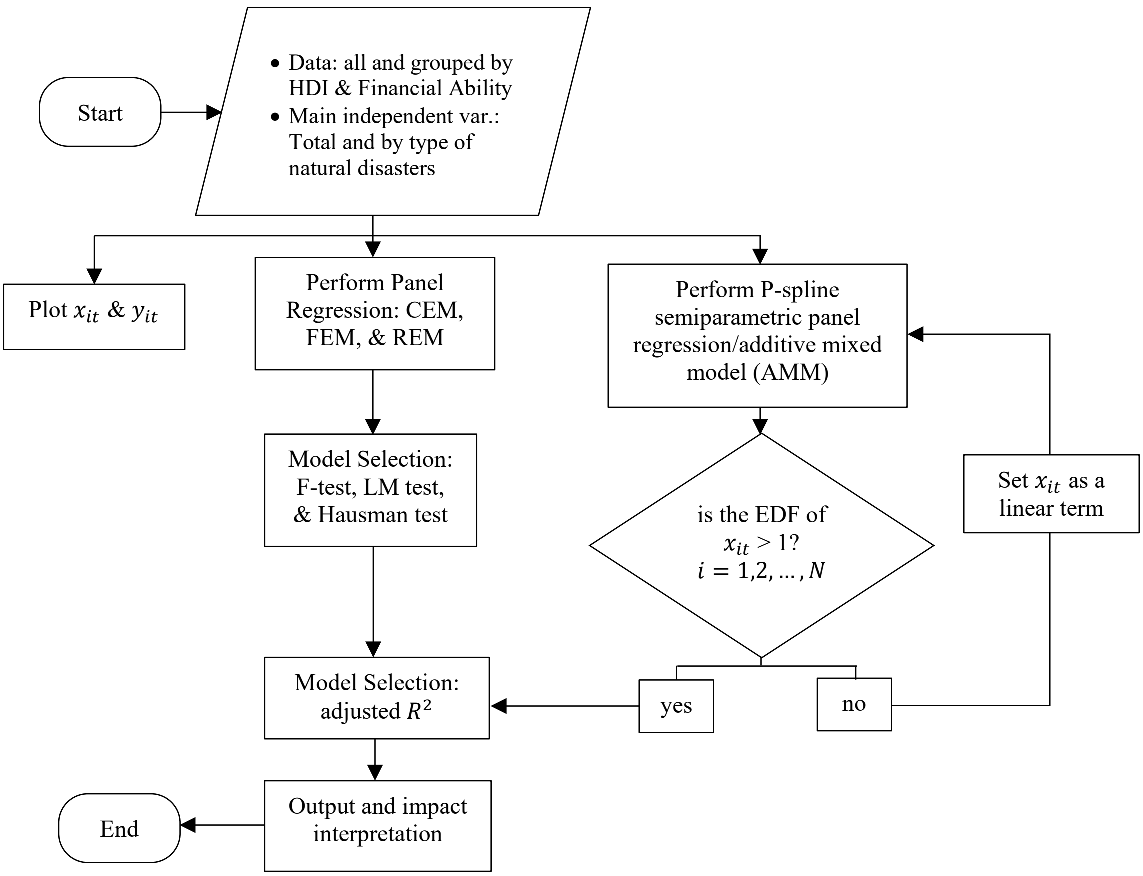
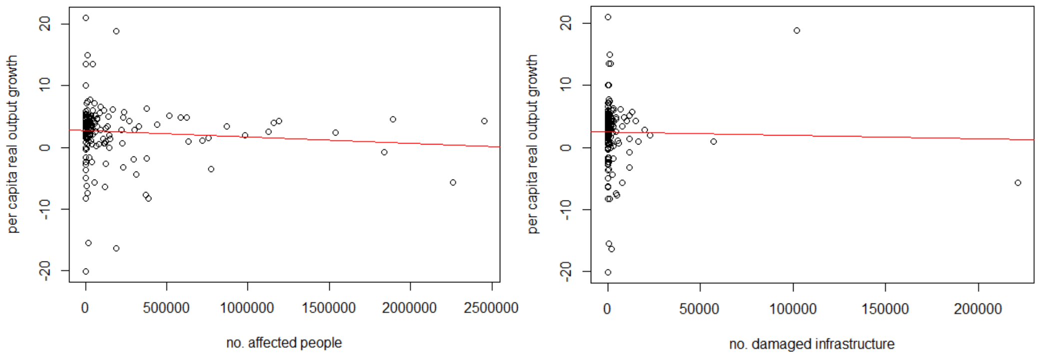


Fig. 1. The analytical procedures

The estimation results of linear panel regression and P-spline semiparametric model are obtained using the *plm* (Croissant & Millo, 2008) and *mgcv* (Wood, 2017) packages in RStudio.

3. RESULTS AND DISCUSSIONS

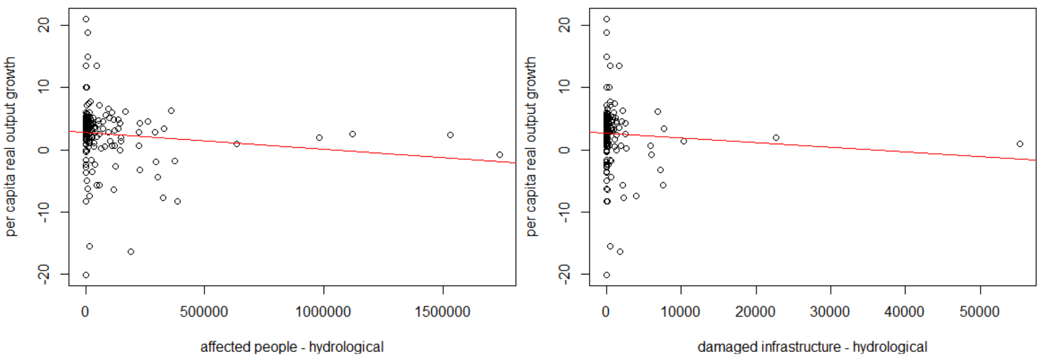
The scatter plots of the total number of affected people and damaged infrastructures caused by natural disasters are presented in Fig. 2. The red fitted line from linear regression is produced to give preliminary visualization of the relationship between explanatory variable and per capita real output growth. This fitted line shows an indication of mild negative impact of natural disasters on economic growth of Indonesia.



(a) (b)

Fig. 2. Scatter plot of the number of affected people (a) and damaged infrastructure (b)

More detail, we also provide the scatter plots of the number of affected people and damaged infrastructures by several types of natural disasters in Fig. 3. Similar to the previous result, all of the figures also show an indication of mild negative impact of natural disasters on economic growth, especially for hydrological natural disaster (Fig. 3a). While for other type of natural disasters, the impact is diminishing that is represented by horizontal fitted line of linear regression.



(a)

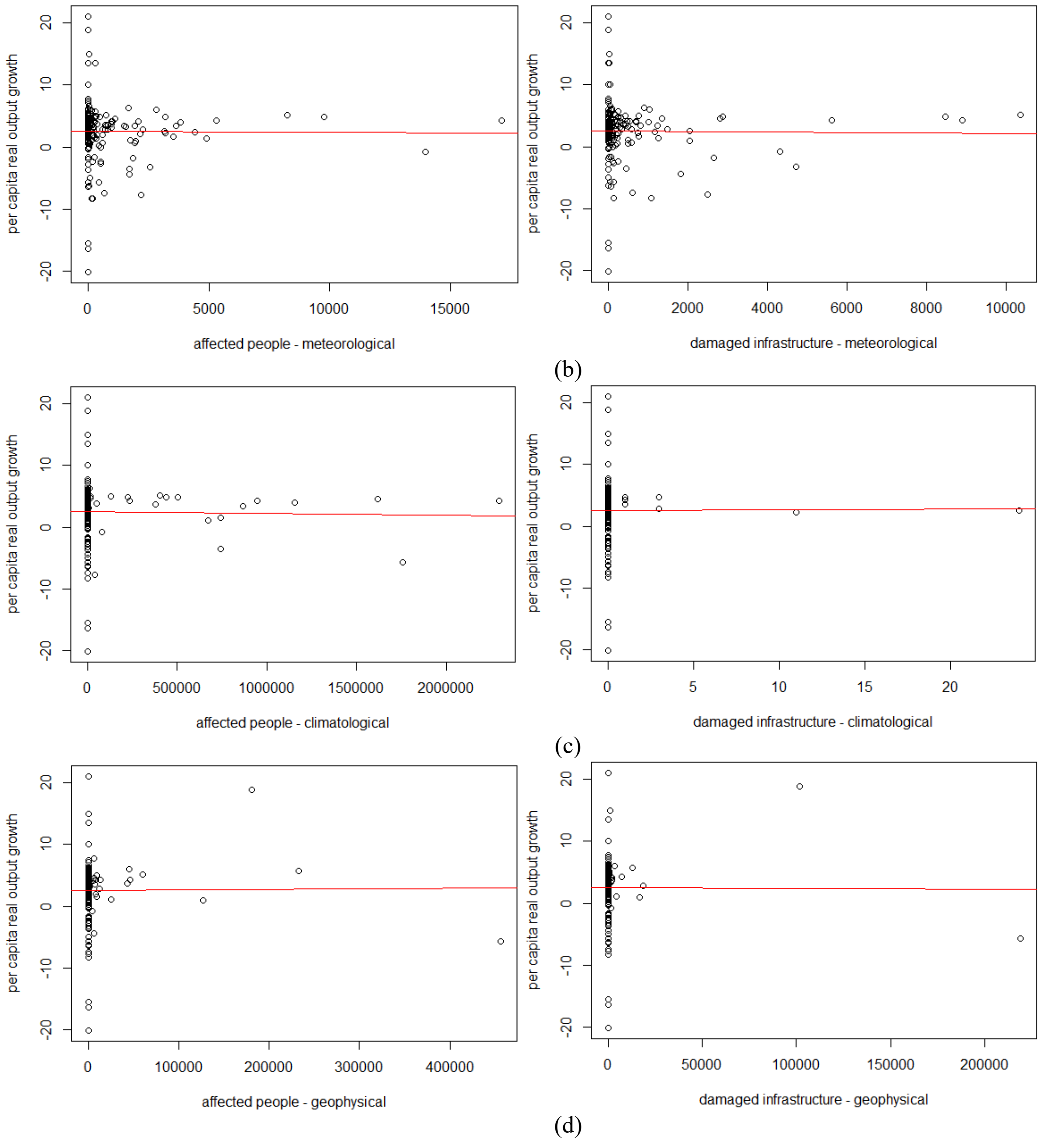


Fig. 3. Scatter plot of the number of affected people (left) and damaged infrastructure (right) caused by hydrological (a), meteorological (b), climatological (c), and geophysical (d) disasters

Fig. 4 provides the scatter plots from the control variables, including the HDI, unexpected budget, inflation, and unemployment rate. Compared to the previous scatter plots, the linear relationship between each control variable and economic growth is more visible. Visually, the positive impact is transmitted by the HDI and inflation. While the variable of unexpected budget and unemployment rate has negative impact on Indonesian economic growth.

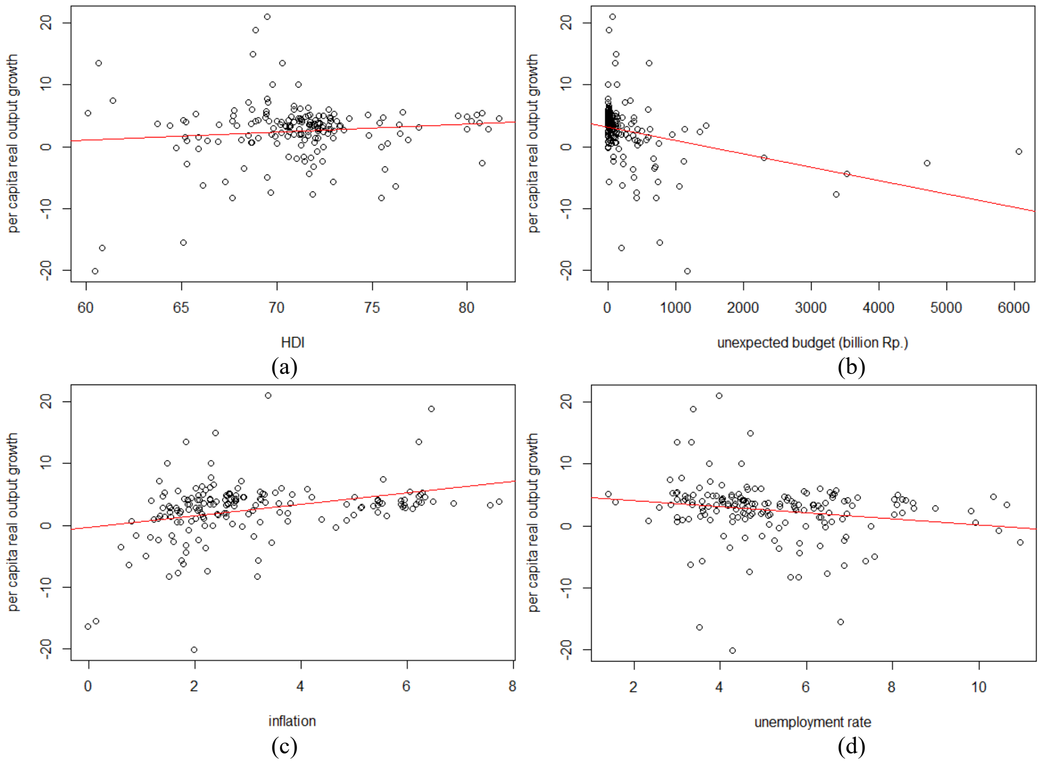


Fig. 4. Scatter plot of the HDI (a), unexpected budget (b), inflation (c), and unemployment rate (d)

Next, we perform estimation for linear panel regression and P-spline semiparametric regression as described in the first and second strategies (Table 1). The estimation results of panel regression for the CEM, FEM, and REM under the two specifications of Model-1 and Model-2 show that the coefficient estimates for all variables in these models are very similar, except for the variable of the total number of affected people and HDI in FEM-1, the variable of the number of affected people by hydrological natural disaster and HDI in FEM-2, and variable of the number of damaged infrastructures caused by hydrological natural disaster in REM-2. Only the number of affected people by meteorological natural disasters has a significant impact on economic growth in the CEM-2 and REM-2. Interestingly, based on the F-test, LM test, and Hausman test, the selected model specification for panel regression is the REM for both specifications of the panel regression, i.e. Model-1 and Model-2.

Table 1. Estimation results from the panel regression and P-spline semiparametric regression

Variables	Panel Regression			
	CEM-1	**CEM-2**	**FEM-1**	**FEM-2**
Intercept	-14.0762*	-14.5644*	-82.0912	-57.5964
People Affected:				
Total	5.3982×10^{-7}		-1.1243×10^{-7}	
Hydrological		1.5294×10^{-6}		7.4366×10^{-7}
Meteorological		0.0005*		0.0005
Climatological		-8.9365×10^{-7}		-5.7207×10^{-7}
Geophysical		2.5013×10^{-6}		5.9639×10^{-6}
Damaged Infrastructure:				
Total	-1.5856×10^{-5}		-1.6569×10^{-5}	
Hydrological		1.0593×10^{-5}		1.516×10^{-5}
Meteorological		-0.0005		-0.0008
Climatological		0.0293		0.0182
Geophysical		-1.4812×10^{-5}		-3.0305×10^{-5}

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HDI	0.1971*	0.2067*	1.1726	0.8234
Unexpected Budget	-0.0011*	-0.0015*	-0.0010*	-0.0014*
Inflation	2.9590*	2.9817*	2.8684*	2.9388*
Inflation^2	-0.2760*	-0.2757*	-0.2925*	-0.2914*
Unemployment Rate	-0.3392	-0.3968	-0.6340	-0.6260
COVID-19	-1.7784*	-1.8410*	-2.2687*	-2.1234*
adj-R square	0.2395	0.23875	0.1434	0.1325

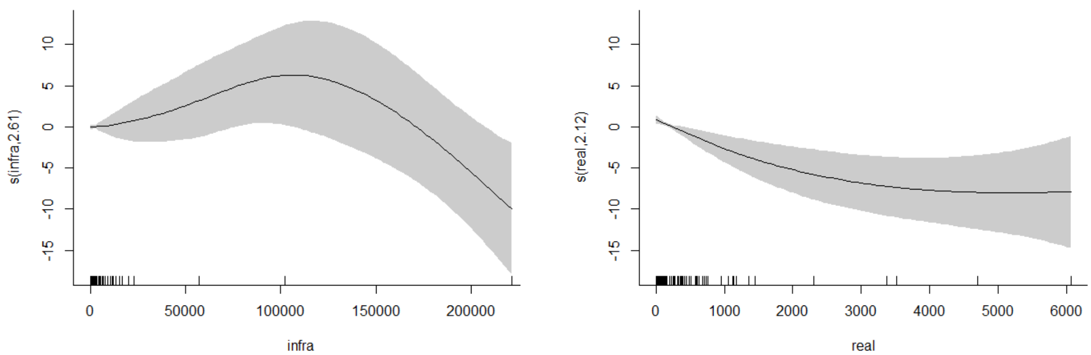
*) denotes statistically significant at α=0.10 and **) denotes the highest value of adjusted R-square

Table 1. (Continued)

Variables	Panel Regression		P-Spline Regression	
	REM-1**	**REM-2****	**AMM-1**	**AMM-2**
Intercept	-14.7768*	-15.3529*	3.1811*	-8.0471
People Affected:				
Total	3.2741 x10^{-7}		0.1855	
Hydrological		1.3785x10^{-6}		0.0001x10^{-2}
Meteorological		0.0006*		0.0003
Climatological		-6.3967x10^{-7}		<0.0001x10^{-2}
Geophysical		5.1741x10^{-6}		-0.0001x10^{-2}
Damaged Infrastructure:				
Total	-1.9609 x10^{-5}		-1.8457	
Hydrological		7.8213 x10^{-6}		-0.0006x10^{-2}
Meteorological		-0.0006		-0.0004
Climatological		0.0200		0.0166
Geophysical		-2.7729x10^{-5}		-0.8196
HDI	0.2137*	0.2230*	0.6823	0.1557
Unexpected Budget	-0.0011*	-0.0015*	-1.2980	-1.6504*
Inflation	2.9057*	2.9588*	8.6502*	9.1620*
Inflation^2	-0.2746*	-0.2770*		
Unemployment Rate	-0.3942	-0.4428	0.6939	0.6485
COVID-19	-1.7512*	-1.8125*	-1.0942	-1.1322
adj-R square	0.2748	0.27915	0.4250**	0.4140

*) denotes statistically significant at α=0.10 and **) denotes the highest value of adjusted R-square

The coefficient estimates for the main explanatory variables produced by P-spline models, i.e AMM-1 and AMM-2, are quite different compared to the coefficient estimates from the panel regression model, especially for the main explanatory variables that have significant P-spline terms or have a strong non-linear relationship. Unfortunately, there is no fixed component of the main explanatory variable that has a significant impact on both models. The main explanatory variables of the number of damaged infrastructures caused by geophysical natural disasters, unexpected budget, inflation, and unemployment rate have significant smooth term or P-spline term in the AMM-1 shown by the functional forms in Fig. 5. These variables have an EDF value more than unity.



(a) (b)

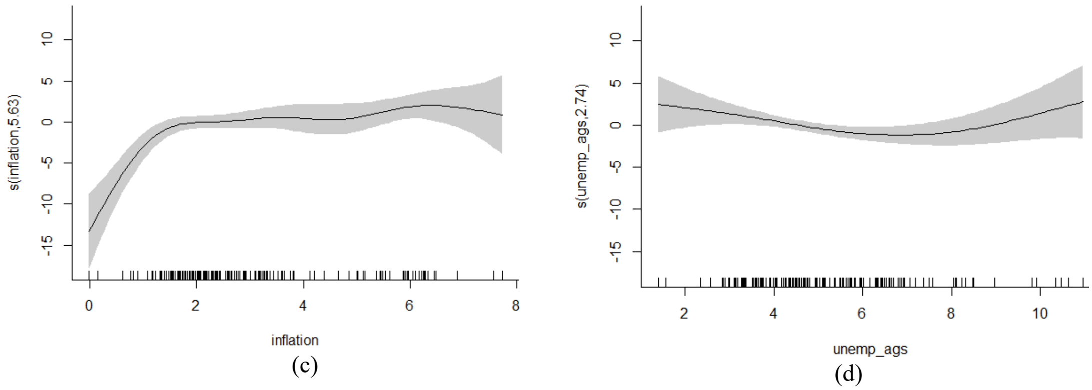


Fig. 5. The Fitted P-spline for the number of damaged infrastructures caused by geophysical natural disasters (a), unexpected budget (b), inflation (c), and unemployment rate (d) on AMM-1

Most of the control variables have a significant impact on Indonesian economic growth in the CEM, FEM, and REM of panel regression, except for the unemployment rate. The HDI in all of the panel regression models has a positive significant impact on economic growth, except in the FEM-1 dan FEM-2. A similar result was also obtained in the previous study by Rahman et al. (2020). This study pre-determines the specification of inflation variable by the quadratic form according to the findings from several studies, e.g. Fischer (1983), Khan and Senhadji (2001), and Kusumatrisna et al. (2022). The result from this study also shows that inflation has a non-linear relationship, an inverted “U-shape”, with economic growth. The unexpected budget and COVID-19 pandemic have a negative impact on economic growth. The global pandemic has caused a contraction of the Indonesian economic about by 1.7-2.1 percent.

Based on the adjusted R-square value in Table 1, the best model in this study is the AMM-1 which has the highest adjusted R-square, i.e. 0.4250 or 42.50 percent. By using this model, further we model the provinces in each group of HDI and the level of financial ability represented by the unexpected budget. The provincial member for each group is depicted by each quadrant in Fig. 6. As an example, the group of low-HDI could be found in quadrants III and IV. The code for provinces in Indonesia is provided in sig.bps.go.id/bridging-kode/index.

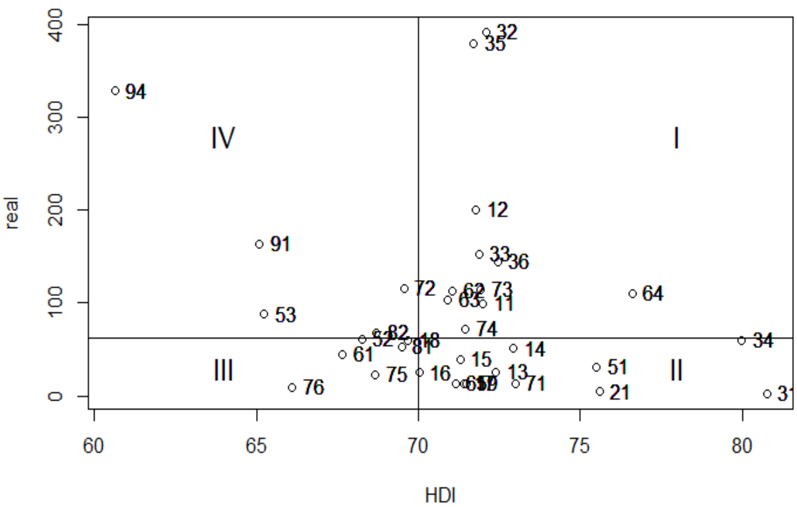


Fig. 6. The provincial member based on the HDI and financial ability level

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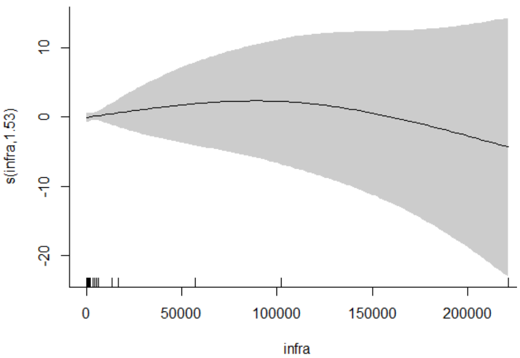
The estimation results for each group of HDI and financial ability are presented in Table 2. Generally, the coefficient estimates from the four groups are quite different indicating that each explanatory variable has different behavior in each group. The total number of affected people in all groups shows a negative impact on economic growth with the highest impact appearing in the low-HDI group, even though the impact is not statistically significant. The total number of damaged infrastructures also produces a negative impact in all groups with the highest impact appearing in the low-financial ability group. This result indicates that the number of damaged infrastructures caused by natural disasters in provinces with low financial ability could lead to a more contraction in economic growth compared to provinces with high financial ability. Note that only this main explanatory variable has significant impact in four groups.

Table 2. Estimation results from P-spline semiparametric regression for each group of HDI and financial ability

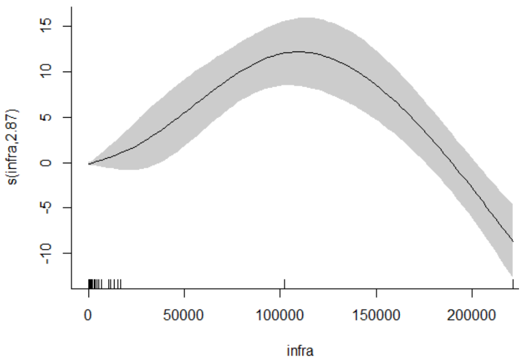
Variables	HDI		Financial Ability	
	Low	High	Low	High
Intercept	10.0565*	1.7226*	5.3622*	1.5699
People Affected:				
Total	$-0.0002x10^{-2}$	$-2.076x10^{-8}$	$-3.597x10^{-7}$	$-2.537x10^{-7}$
Damaged Infrastructure:				
Total	-0.6384	$1.762x10^{-5}$	-2.8071*	$1.075x10^{-5}$
Inflation	7.0912	0.8229*	-0.0152	5.2967
Unemployment Rate	-1.4041	-0.0415	-0.1860	-1.0105
COVID-19	-2.3615	-2.7847*	-1.6642*	-0.4571
adj-R square	0.2290	0.352	0.576	0.254

*) denotes statistically significant at $\alpha = 0.10$

The four groups above have a different significance of smooth terms. The smooth term of the total number of damaged infrastructure and inflation are statistically significant in low-HDI and low-financial ability groups. In the high-financial ability group, the statistically significant smooth terms are inflation and unemployment. While in the high-HDI group, the only significant smooth term is the unemployment variable. For a comparison, we provide the visualization of the fitted P-spline for the total number of damaged infrastructures in low-HDI and low-financial ability groups in Fig. 7.



(a)



(b)

Fig. 7. The fitted P-spline for the number of damaged infrastructures caused by natural disasters in low-HDI (a) and low-financial ability (b) groups

4. CONCLUSION AND RECOMMENDATIONS

The estimation results from several models show that the P-spline semiparametric models are better for capturing the variation of the economic growth indicated by the higher adjusted R-square produced by these two models. Most of the main explanatory variables, either globally or by type, in linear panel regression and P-spline models are not statistically significant in the form of fixed terms. However, in the form of smooth terms provided by the P-spline models, we found some significant variables. These results indicate the nature of the non-linear relationship between natural disasters and economic growth.

The best model obtained in this study is the AMM-1 which has the global number of affected people and damaged infrastructure as the main explanatory variables instead of specifying it by type of natural disaster as provided in the AMM-2. This result indicates that natural disasters by its type separately could not show a significant impact on the economic growth of Indonesia. The modeling process for each group based on HDI and financial ability could reveal the variation of impact behavior from natural disasters indicating that each provincial group has a different impact transmitted by the natural disaster. Based on the coefficient estimates from each group, we could provide the insight for Indonesian government to pay more attention to the impact of the number of damaged infrastructures caused by natural disasters in low-HDI and low-financial ability groups and impact of the number of affected people by natural disasters in low-HDI.

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6. CONFLICT OF INTEREST STATEMENT

The authors declared that they have no conflicts of interest to disclose.

7. AUTHORS' CONTRIBUTIONS

Taly Purwa: Data curation; Formal Analysis; Methodology; Resources; Software; Validation; Visualization; Writing – original draft; **Wahyu Wibowo**: Conceptualization; Data curation; Formal Analysis; Funding acquisition; Investigation; Methodology; Project administration; Validation;Writing – review & editing; **Elya Nabila Abdul Bahri**: Conceptualization; Formal Analysis; Investigation; Methodology; Validation; Writing – review & editing.

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