

Poverty and Social Welfare: An Autoregressive Vector Panel Analysis of Social Work Interventions in Indonesia, Malaysia, and the Philippines (1996-2022)

Willya Achmad¹, Yogie Prawira², Hindina Maulida², and Fadriyansyah Munggaran³

¹Faculty Social Science and Political Science, Universitas Pasundan, Indonesia, 40261

²Faculty Social Science and Political Science, Universitas Tidar, Magelang, Indonesia, 56116

³Postgraduate Program, Faculty of Social and Political Sciences, Padjadjaran University, Bandung, Indonesia, 40132

E-mail: willyaachmad@unpas.ac.id; yogieprawira@untidar.ac.id; hindina@untidar.ac.id; fadriyansyah19001@mail.unpad.ac.id

ABSTRACT

This study investigates the implementation and efficacy of macro-level social work interventions in Indonesia, Malaysia, and the Philippines. Using World Bank secondary data (1996–2022), the research evaluates poverty alongside variables representing macro interventions: investment levels, labor force participation, and school enrollment. Panel Vector Autoregression (PVAR) analysis reveals that historical investment strongly drives current investment, creating a continuous growth cycle. Paradoxically, increased investment negatively impacts labor force participation, poverty levels, and school enrollment, indicating that economic growth can trigger adverse social consequences. Furthermore, the Unrestricted Cointegration Rank Test (Trace) demonstrates no long-term relationship between the variables, suggesting the model's limitations for long-term forecasting. Impulse Response Function (IRF) results confirm that while variables influence each other in subsequent periods, these impacts diminish over time. The findings highlight that while investments drive economic growth in these nations, they do not automatically alleviate poverty. Unfairly allocated investments may even prove counterproductive to educational and welfare goals. Given the inherently unstable relationship between economics and society, poverty remains a multifaceted challenge. Ultimately, policy-makers must balance economic progress with social welfare, ensuring that economic policies actively complement social policies.

Keywords: poverty; investment; labor force participation; school enrollment rates

Kemiskinan dan Kesejahteraan Sosial: Analisis Panel Vektor Autoregresif Intervensi Pekerjaan Sosial di Indonesia, Malaysia, dan Filipina (1996-2022)

ABSTRAK

Penelitian ini menginvestigasi implementasi dan efektivitas intervensi pekerjaan sosial tingkat makro di Indonesia, Malaysia, dan Filipina. Menggunakan data sekunder Bank Dunia (1996–2022), penelitian ini mengevaluasi kemiskinan bersama dengan variabel yang mewakili intervensi makro: tingkat investasi, partisipasi angkatan kerja, dan partisipasi sekolah. Analisis Panel Vector Autoregression (PVAR) mengungkapkan bahwa investasi masa lalu sangat mendorong investasi saat ini, sehingga menciptakan siklus pertumbuhan yang berkelanjutan. Paradoksnya, peningkatan investasi berdampak negatif pada partisipasi angkatan kerja, tingkat kemiskinan, dan partisipasi sekolah, yang mengindikasikan bahwa pertumbuhan ekonomi dapat memicu konsekuensi sosial yang merugikan. Lebih lanjut, hasil Unrestricted Cointegration Rank Test (Trace) menunjukkan tidak adanya hubungan jangka panjang antarvariabel, yang mengisyaratkan keterbatasan model ini untuk peramalan jangka panjang. Hasil Impulse Response Function (IRF) mengonfirmasi bahwa meskipun variabel-variabel saling memengaruhi pada periode berikutnya, dampak ini akan menurun seiring berjalannya waktu. Temuan ini menyoroti bahwa meskipun investasi mendorong pertumbuhan ekonomi di negara-negara tersebut, hal itu tidak serta-merta mengentaskan kemiskinan. Investasi yang tidak dialokasikan secara merata bahkan dapat menjadi kontraproduktif terhadap tujuan pendidikan dan kesejahteraan. Mengingat hubungan antara ekonomi dan masyarakat yang pada dasarnya tidak stabil, kemiskinan tetap menjadi tantangan yang multifaset. Pada akhirnya, pembuat kebijakan harus menyeimbangkan kemajuan ekonomi dengan kesejahteraan sosial, guna memastikan bahwa kebijakan ekonomi secara aktif melengkapi kebijakan sosial.

Kata Kunci: kemiskinan; investasi; partisipasi angkatan kerja; angka partisipasi sekolah

INTRODUCTION

Comparative Poverty refers to two main concepts in poverty studies, namely Two types of poverty: absolute and relative (Decerf, 2021). Absolute poverty is the state in which a person's income is insufficient to meet their fundamental necessities, which include clothes, food, and shelter (Gweshengwe & Hassan, 2020). Meanwhile, Relative Poverty occurs when someone lives above the poverty line but is still below the economic standards of the surrounding community, often as a result of uneven development policies (Sun et al., 2022). Understanding these differences is important in defining and measuring poverty in various contexts, as well as in designing policies to address different types of poverty (Redondo-Sama et al., 2020). Interventions to address Absolute Poverty focus more on increasing access to basic resources, while interventions for Relative Poverty focus more on issues such as inequality and access to opportunities (Beech et al., 2021).

In 2023, Indonesia will be ranked sixth in the country with the highest poverty rate in Southeast Asia (Hill, 2021). In 2018, the proportion of Filipinos living below the poverty line was 4.7%, representing a decrease of 5.8 percentage points from 10.5% in 2009 (Barletta et al., 2022). Meanwhile, Malaysia has the lowest percentage of people living below the poverty line in Southeast Asia. In 2015, the percentage of the Malaysian population living below the poverty line almost reached 0%, decreasing from 0.1% in 2011. Thus, this data shows that there is an increase in general prosperity in the Southeast Asia region, although there are still challenges that must be faced (Deutsch et al., 2020; Yuda & Kühner, 2023).

The various challenges faced by social work education in Indonesia include development of relevant theoretical models, curriculum standardization, learning process, fieldwork, and professional credentialing (Susilowati et al., 2020). The social work education in Malaysia is affected by factors like westernization, professionalism, colonial history, multiculturalism, and governance. Community kitchens have been found to be used as one of the forms of social work service delivery in the Philippines amid the pandemic. Generally, mental health issues have been identified as one of the main challenges in Southeast Asian countries owing to the lack of adequate human resources and mental health facilities (Das et al., 2023). Thus,

psychosocial interventions that are accessible and culturally relevant are key (Easterbrook & Hadden, 2021; Maddock et al., 2021).

Social Work interventions at the macro level involve interventions available on a large scale that impact entire communities and systems of care (Dopp & Lantz, 2020). The macroeconomic variables that represent these interventions can vary depending on the context and objectives of the intervention. Several macroeconomic variables that are often used based on research include investment, work participation rates, and school enrollment rates. The level of investment in an economy can affect employment and social welfare. In addition, the Labor Force Participation Rate a measure of the proportion of the population that is employed or seeking employment, can indicate that more people have jobs, which can contribute to social well-being.

Investment is the main driving force of economic growth. By increasing investment, a country can increase its output and national income. Investment can create jobs and increase productivity, which can ultimately reduce poverty (Dopp & Lantz, 2020). Investment in the form of infrastructure development or industrial expansion can create new jobs. With new jobs, people who previously did not have jobs can earn income. This can directly reduce poverty levels. Investment can also increase productivity. Investments in technology and education can improve workers' skills and knowledge, so they can produce more output (Widarni & Bawono, 2022). With higher productivity, workers can earn higher wages, which can help reduce poverty (Zou et al., 2022).

Apart from that, economic growth can also increase government income through taxes, which can be used for social programs to help the poor. Investment plays an important role in reducing poverty. Through job creation, increased productivity, and economic growth, investment can help lift people out of poverty. Therefore, it is important for the government and private sector to invest in areas that can provide the greatest benefits for poor people (Omar & Inaba, 2020).

The percentage of the population that is either employed or seeking for employment is known as the labor force participation rate. It is an important indicator of a country's economic health. Poverty, on the other hand, is a condition where an individual or community does

not have sufficient financial and material resources. A high labor force participation rate usually means that more people have jobs, which can help reduce poverty (Wachter, 2020). Work provides income, which can be used to meet basic needs and improve the quality of life. Therefore, increasing labor force participation can contribute to reducing poverty rates. On the other hand, if the labor force participation rate is high but the unemployment rate is also high, this could be a problem. Unemployment means that someone who wants to work cannot find a job, which can lead to poverty. Therefore, it is important not only to increase labor force participation, but also to create jobs (Ningrum et al., 2020).

Education and training can play an important role in increasing labor force participation and reducing poverty. With the right knowledge and skills, individuals have a better chance of finding a good job. Therefore, investment in education and training can help increase labor force participation and reduce poverty (Assaad et al., 2020). Overall, there is a strong relationship between labor force participation rates and poverty. Increasing labor force participation, reducing unemployment, and investing in education and training can help reduce poverty. Therefore, policies aimed at achieving this goal can have a significant positive impact in fighting poverty (Omar & Inaba, 2020).

School enrollment rates refer to the percentage of children and young people who are enrolled and attending school. Poverty, on the other hand, is a condition where an individual or family does not have enough material and financial resources. Education is one of the most effective tools to fight poverty. With good education, individuals have a greater chance of getting a good job and achieving economic stability (Mhlana, 2021). Therefore, high school enrollment rates can contribute to reducing poverty levels. However, poverty is often a barrier to access to education. Children from poor families may not be able to afford to attend school because of the cost of tuition, books and uniforms. Therefore, it is important to ensure that education is available to all, regardless of their economic background (Cohen et al., 2021).

Investments in education, such as school construction, teacher training, and scholarship programs, can help increase school enrollment rates. With more children attending school, we can expect to see a reduction in poverty rates in

the future (Evans & Mendez Acosta, 2021). Overall, there is a strong relationship between school enrollment rates and poverty. Increasing access to education and investment in education can help reduce poverty. Therefore, policies aimed at achieving this goal can have a significant positive impact in fighting poverty (Raghupathi, 2020).

Based on previous research, Significant advancements have been made in the economic expansion of Southeast Asian nations including Indonesia, Malaysia, and the Philippines (Basri & Hill, 2020; Moey et al., 2020; Triatmanto et al., 2023). Despite this, the problems of poverty and income inequality are still persistent. Economic growth over the last half century has raised living standards, but not all social indicators have shown the same improvement (Hickel & Hallegatte, 2022). However, there still seems to be a lack of comprehensive studies comparing the effectiveness of social work interventions in Indonesia, Malaysia, the Philippines in overcoming poverty and inequality (Muhtar et al., 2023). Although economic indicators and poverty rates have been researched, the impact of social work interventions on these issues has not been well documented (Knapp & Wong, 2020).

One of the most prominent research gaps in this area is the lack of consideration given to the incorporation of macroeconomic variables in a framework of social work to understand the issue of poverty. Prior works have largely focused on examining investment, labor force participation, and education participation with an economic approach rather than viewing them in terms of macro-social interventions. Moreover, few prior researchers have considered employing dynamic models like PVAR in studying the inter-relationship of these variables. Furthermore, comparative analysis involving Indonesia, Malaysia, and the Philippines has not been conducted extensively, especially in light of varying socioeconomic environments.

The aim of this research is to understand how social work interventions have been implemented in Indonesia, Malaysia, and the Philippines, to what extent they are effective, and how they can be improved. The research also explores differences in the approaches taken by each country and what lessons can be learned from each. It will contribute to existing knowledge by providing new insights into the

role of social work in poverty alleviation and income redistribution efforts in Southeast Asia.

METHODS

This study utilizes secondary data from the World Bank covering the period 1996–2022, focusing on poverty as the main variable alongside school enrollment, labor force participation, and investment as proxies for macro-level social work–related interventions. The involvement of social work practices in Indonesia, Malaysia, and the Philippines is synthesized through these indicators, as they reflect government and institutional efforts in social protection, human capital development, and community welfare, which are central to social work at the structural level. Despite differences in national contexts, these variables are considered comparable due to the standardized measurement of World Bank data and the shared presence of social policy initiatives across the three countries during the study period. The Panel Vector Autoregression (PVAR) approach is employed to analyze the dynamic and interdependent relationships among variables, allowing all variables to be treated as endogenous. Although the number of countries is limited, the long time span provides sufficient observations, making PVAR appropriate for capturing temporal dynamics and short-term interactions between poverty and macro-level interventions. This study examines the association between these variables. Researchers can comprehend how changes in one variable over time impact changes in other variables by using this strategy. The variables poverty (P), investment level (I), labor force participation rate (TPAK), and

school participation rate (APS) are used in the Panel Vector Autoregression Model (PVAR). For each individual *i* and time *t* it can be written as follows:

$$\begin{aligned} P_{it} &= \alpha_{1i} + \beta_{11}P_{i,t-1} + \beta_{12}I_{i,t-1} + \beta_{13}TPAK_{i,t-1} + \beta_{14} \\ I_{it} &= \alpha_{2i} + \beta_{21}P_{i,t-1} + \beta_{22}I_{i,t-1} + \beta_{23}TPAK_{i,t-1} + \beta_{24} \\ TPAK_{it} &= \alpha_{3i} + \beta_{31}P_{i,t-1} + \beta_{32}I_{i,t-1} + \beta_{33}TPAK_{i,t-1} + \beta_{34} \\ APS_{it} &= \alpha_{4i} + \beta_{41}P_{i,t-1} + \beta_{42}I_{i,t-1} + \beta_{43}TPAK_{i,t-1} + \beta_{44} \end{aligned}$$

Where, α_{ji} is the individual fixed effect for each variable *j*. β_{jk} is the regression coefficient of variable *k* at *t*-1 against variable *j* at *t*. ϵ_{jit} is random error. Table 1 displays variable descriptions.

With the data, we ran a stationarity test using the Augmented Dickey Fuller (ADF) technique. In case the data is not level-stationary, we subject it to a differencing procedure. Next, we use the least Akaike Information Criterion (AIC) value to find the ideal lag duration. We estimate the VAR model once the ideal lag duration has been established. The Ordinary Least Square (OLS) approach was used to estimate the VAR model for each equation independently. In order to determine the reciprocal effect between the variables examined in this study, we also performed the Causality Unrestricted Cointegration Rank Test (Trace). Lastly, we monitor how shocks from one variable affect other variables using the Impulse Response Function (IRF) test.

RESULTS AND DISCUSSION

Statistical descriptions provide an overview of the data we have, including central measures such as mean and median, measures of spread

Table 1. Variable Description

Variable	Description	Unit of Analysis
Poverty	The percentage of the population that lives below the poverty line is referred to as the poverty rate.	Percentage (%)
Investment Level	Investment level refers to the amount of investment made in a given time period, usually measured as a percentage of GDP.	Percentage (%)
Rate of Labor Force Participation	The percentage of people in the working age group who are either employed or seeking for employment is known as the labor force participation rate.	Percentage (%)
School Enrollment Rates	The school enrollment rate is the percentage of the population in a certain age group who are enrolled in school.	Percentage (%)

Source: Compiled by Authors

such as standard deviation and quartiles, and forms of data distribution such as skewness and kurtosis. This understanding is important to know how a Variable behaves before inserting it into a Panel Vector Autoregression (PVAR) model. Some model assumptions, such as stationarity and homoscedasticity, can be checked using statistical descriptions. If these assumptions are not met, we may need to perform data transformations or consider alternative models. Additionally, statistical descriptions can help us identify outliers that might influence model estimates. These outliers can be handled in various ways, based on the analysis's goals and the situation. Once the PVAR model is estimated, the statistical description of the Variables can help in the interpretation of the coefficients. Table 2 provides statistical descriptions.

From the descriptive statistics in Table 2, we can see that the average investment is 3.22 with a variation of 1.79. Compared to a normal distribution, the investment distribution is tilted to the right and has larger tails, as indicated by positive skewness and kurtosis greater than 3. The highest observed investment value is 9.34 and the lowest is 1.17. For labor force participation, the average is 65.53% with a variation of 3.14%. Compared to a normal distribution, the labor force participation distribution is left-skewed and has lighter tails, as indicated by

negative skewness and kurtosis of less than 3. The highest labor force participation observed was 70.61% and the lowest was 56.91%. The average poverty level is 49.35% with a variation of 25.25%. The distribution of poverty rates is skewed to the left and has lighter tails than a normal distribution, as indicated by negative skewness and kurtosis of less than 3. The highest observed poverty rate is 70.61% and the lowest is 2.30%. Finally, for school participation, the average is 104.88% with a variation of 6.22%. The distribution of school participation is skewed to the left and has lighter tails than a normal distribution, as indicated by negative skewness and kurtosis of less than 3. The highest school participation observed was 115.96% and the lowest was 90.61%.

Method	Statistic	Prob.**	Crosssections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.31491	0.0236	4	320
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.33423	0.0369	4	320
ADF - Fisher Chi-square	6.81685	0.0165	4	320
PP - Fisher Chi-square	7.48767	0.0385	4	320

Figure 1. Root Unit Test

Source: Compiled by Authors

The Dickey-Fuller or Augmented Dickey-Fuller tests are examples of unit root tests that are used to determine whether or not a time se-

Table 2. Descriptive Statistics

	Investment	Labor Force Participation	Poverty	School Enrollment
Mean	3.220110	65.52972	49.35020	104.8789
Median	3.132833	64.05000	66.10000	105.3109
Maximum	9.340472	70.60800	70.60800	115.9636
Minimum	1.166109	56.91400	2.300000	90.60991
Std. Dev.	1.789228	3.140324	25.25234	6.223074
Skewness	1.247882	-0.113813	-0.799386	-0.151806
Kurtosis	4.516370	2.016265	1.890516	1.970989
Jarque-Bera	28.78274	3.440974	12.78120	3.884772
Probability	0.000001	0.178979	0.001677	0.143361
Sum	260.8289	5307.907	3997.366	8495.193
Sum Sq. Dev.	256.1070	788.9309	51014.46	3098.132
Observations	81	81	81	81

Source: Compiled by Authors

ries is stationary. This is significant in the context of PVAR as the model presupposes that every variable in the system is stationary. The results of the PVAR model estimate may be skewed and inconsistent if the variable is not steady. This is Figure 1: the unit root test.

Figure 1. unit root test results demonstrate the steady nature of the data. The statistical value in the Levin, Lin, and Chu test is 0.314991, with a probability of 0.0236. For this test, the assumption that every series has a unit root is the null hypothesis. We reject the null hypothesis (i.e., not all series have a unit root) since the p-value is less than 0.05. Additionally, the statistical value in the Im, Pesaran, and Shin tests is -0.33423, with a probability of 0.0369. For this test, the assumption that every series has a unit root is the null hypothesis. We reject the null hypothesis since the p-value is less than 0.05, indicating that not all series have a unit root. The statistical value in the ADF - Fisher Chi-square test is 6.81685, with a probability of 0.0165. For this test, the assumption that every series has a unit root is the null hypothesis. We reject the null hypothesis (i.e., not all series have a unit root) since the p-value is less than 0.05. Lastly, the statistical value for the PP-Fisher Chi-square test is 7.48767, with a probability of 0.0385. For this test, the assumption that every series has a unit root is the null hypothesis. We reject the null hypothesis (i.e., not all series have a unit root) since the p-value is less than 0.05. The test findings indicate that the data series is stationary overall.

An essential component of PVAR (Panel Vector Autoregression) model analysis is the Lag Order Selection Criteria. The amount of time periods we look backward in the model is called the order of lag. Selecting the proper lag sequence is crucial as it influences the model's efficacy and precision. All variables are regarded as endogenous in the PVAR model, although in order to separate the effects of exogenous disruptions on the system, identification limits based on theoretical models or statistical techniques may be used. In this model, selecting the appropriate lag order is an important step in impulse response analysis. There are several criteria commonly used in selecting lag orders, as the Hannan-Quinn Criterion (HQC), the Schwarz Information Criterion (SIC), and the Akaike Information Criterion (AIC). Using this criterion, models with varying lag orders are compared and the model with the fewest parameters that best explains the data is chosen.

In general, selecting an appropriate lag order can help ensure that the PVAR model provides an unbiased and efficient estimate of the dynamic relationships between variables in the panel. The PVAR Lag Order Selection Criteria are displayed in Table 3.

Table 3. PVAR Lag Order Selection Criteria

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-	NA	183	23.4	23.5	23.5
	876.		731.	727	963	220
	227		9	3	3	9
1	-	797.9430*	3.15	12.5	13.1	12.7
	448.		661	002	182	469
	758		4*	2*	1*	8*
2	-	16.10385	3.80	12.6	13.7	13.1
	439.		389	828	952	270
	608		3	8	8	5
	-					

Source: Compiled by Authors

The model with lag 1 is the best model, according to the outcomes of the PVAR lag selection criteria that you specify. For this model, the Log Likelihood (LogL) value is -448.7581, the LR value is 797.9430, the FPE value is 3.156614, the AIC value is 12.50022, the SC value is 13.11821, and the HQ value is 12.74698. All these values are marked with an asterisk (*), which usually indicates that this model is the best model based on those criteria. Therefore, the PVAR model with lag 1 provides the best explanation of the data with the smallest number of parameters and should be considered for further analysis.

Estimating Panel Vector Autoregression (PVAR) is a crucial step in analyzing the dynamic connections among variables in panel data. All variables are regarded as endogenous in the PVAR model, although in order to separate the effects of exogenous disruptions on the system, identification limits based on theoretical models or statistical techniques may be used. PVAR estimations give information about the short- and long-term effects of changes in one time-series variable on other variables. Panel Vector Autoregression Estimates are displayed in Table 4.

Table 4. Panel Vector Autoregression Estimates

	Investment	Labor Force Participatio	Poverty	School Enrollment
Investment(-1)	0.924964	-0.117581	-0.077793	0.047730
	(0.12905)	(0.17048)	(0.28529)	(0.27385)
	[7.16722]	[-0.68971]	[-0.27268]	[0.17429]
Labor Force Participatio(-1)	-0.081524	0.897840	0.056831	0.729444
	(0.11005)	(0.14537)	(0.24327)	(0.23352)
	[-0.74080]	[6.17610]	[0.23361]	[3.12367]
Poverty(-1)	-0.058823	0.026970	0.992589	-0.086265
	(0.05895)	(0.07788)	(0.13032)	(0.12510)
	[-0.99780]	[0.34633]	[7.61657]	[-0.68959]
School Enrollment(-1)	-0.014245	0.017967	-0.033953	1.224171
	(0.05735)	(0.07576)	(0.12678)	(0.12170)
	[-0.24838]	[0.23716]	[-0.26781]	[10.0590]
C	1.564504	2.059929	-4.025043	3.668999
	(2.55271)	(3.37210)	(5.64299)	(5.41679)
	[0.61288]	[0.61087]	[-0.71328]	[0.67734]
R-squared	0.861416	0.918536	0.996480	0.944517
Adj. R-squared	0.844617	0.908662	0.996053	0.937792
Sum sq. Resids	34.98980	61.05720	170.9840	157.5509
S.E. equation	0.728113	0.961826	1.609555	1.545036
F-statistic	51.28049	93.02221	2335.449	140.4438
Log likelihood	-77.82921	-98.70750	-137.3235	-134.2552
Akaike AIC	2.315446	2.872200	3.901959	3.820138
Schwarz SC	2.593544	3.150299	4.180057	4.098236
Mean dependent	3.213100	65.58036	48.89365	104.5582
S.D. dependent	1.847131	3.182517	25.62039	6.194612

Source: Compiled by Authors

'Investment' in the current period will rise by 0.924964 units for every unit increased in the previous period, decrease 'Labor Force Participation' by 0.117581 units, decrease 'Poverty' by 0.077793 units, and increase 'School Enrollment' by 0.047730 units . Likewise, a 1 unit increase in 'Labor Force Participation', 'Poverty', and 'School Enrollment' in the previous period

will have its respective effect on all Variables in the current period.

R-squared value and Adj. R-squared shows the extent to which the model explains variations in the data. The model explains approximately 86.14% of the variation in 'Investment', 91.85% of the variation in 'Labor Force Participation', 99.65% of the variation in 'Poverty',

and 94.45% of the variation in ‘School Enrollment’.

The F-statistic value indicates the overall significance of the model, with higher values indicating that the model significantly explains variation in the data. AIC and SC values were used to compare models, with the model with the lowest value being preferred. Log likelihood values are also used to compare models, with models with higher values being preferred.

Unrestricted Cointegration Rank Test (Trace) plays an important role in Panel Vector Autoregression (PVAR) analysis. The number of cointegration vectors in the system is ascertained using this test. A cointegrating vector is a linear combination of variables that are stationary, even though the original variables may be non-stationary. Table 5 shows the Unrestricted Cointegration Rank Test (Trace).

Table 5. The Trace Unrestricted Cointegration Rank Test

Hypothesized	Trace		0.05	
No. of CE(s)	Eigen value	Statistic	Critical Value	Prob.**
None	0.303497	38.79850	47.85613	0.2684
At most 1	0.127775	12.75736	29.79707	0.9023
At most 2	0.034715	2.914386	15.49471	0.9706
At most 3	0.005133	0.370522	3.841466	0.5427

Source: Compiled by Authors

A p value larger than 0.05 at all levels indicates that there is no cointegration vector in the model, which is consistent with the findings of the Unrestricted Cointegration Rank Test (Trace). We cannot rule out the null hypothesis that there are at most n cointegrating vectors at each level as the eigenvalues and Trace statistics at each level are less than their critical values. This demonstrates that there is no sustained link between the model's variables.

Impulse Response Function (IRF) shows how a variable reacts to shocks or changes in other variables in the model. In this context, IRF shows how investments react to changes in labor force participation, poverty, and school

enrollment. The Impulse Response Function (IRF) can be accessed in the Annex.

From the IRF results, it can be seen that the investment response to itself in the first period was 0.728113 and decreased over time. This shows that a shock to investment will have a positive impact on investment itself in the following period, but the impact will decrease over time. Meanwhile, investment responses to labor force participation, poverty and school enrollment are generally negative, indicating that positive shocks to these variables tend to reduce investment. However, this effect also diminishes over time. A positive shock to labor force participation in the second period produces an investment response of -0.111207, but this response decreases to -0.168393 in the tenth period.

From the IRF results, it can be seen that the response of labor force participation to itself in the first period was 0.958791 and decreased over time. This shows that a shock to labor force participation will have a positive impact on labor force participation itself in the following period, but the impact will decrease over time. Meanwhile, the response of labor force participation to investment is generally negative, indicating that positive shocks to investment tend to reduce labor force participation. However, this effect also diminishes over time. The positive shock to investment in the second period produces a labor force participation response of -0.156507, but this response decreases to -0.254484 in the tenth period. Additionally, the response of labor force participation to poverty and school enrollment changes from positive to negative over time, indicating that the effects of these variables on labor force participation change over time.

From the IRF results, it can be seen that the poverty response to itself in the first period was 1.517744 and decreased over time. This shows that a shock to poverty will have a positive impact on poverty itself in the following period, but the impact will decrease over time. Meanwhile, the poverty response to investment is generally positive at the start of the period but turns negative over time, indicating that positive shocks to investment tend to increase poverty initially but this effect reverses over time. In addition, the response of poverty to labor force participation and school enrollment is generally positive, indicating that positive shocks to these variables tend to increase

poverty. However, this effect also diminishes over time.

From the IRF results, it can be seen that the school's enrollment response to itself in the first period was 1.467428 and decreased over time. This suggests that a shock to school enrollment will have a positive impact on school enrollment itself in the following period, but the impact will diminish over time. Meanwhile, the response of school enrollment to investment is generally negative, indicating that a positive shock to investment tends to reduce school enrollment. However, this effect also diminishes over time. The positive shock to investment in the second period produces a school enrollment response of -0.533682, but this response increases to -0.405932 in the tenth period. In addition, the response of school enrollment to labor force participation and poverty is generally positive, indicating that positive shocks to these variables tend to increase school enrollment. However, this effect also diminishes over time. We present a visualization of the IRF in Figure 2.

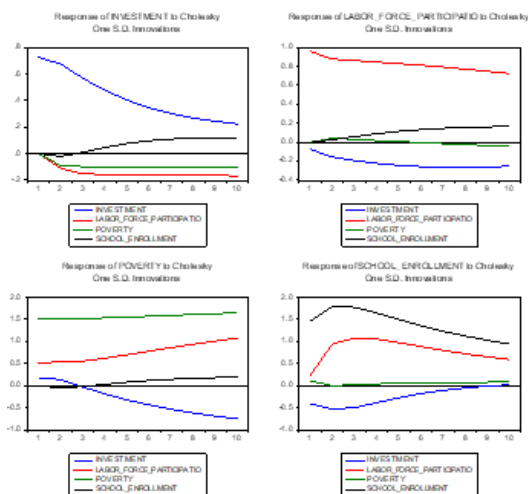


Figure 2. Impulse Response Function (IRF)

This study highlights that macro-level social work interventions in Indonesia, Malaysia, and the Philippines are represented by economic variables such as investment levels, labor force participation, and school enrollment. While these three countries have demonstrated significant economic progress in recent decades, the challenges of poverty and income inequality remain key issues requiring diverse policy approach.

In terms of poverty rates, Malaysia performed best, with the percentage of its population living below the poverty line nearly reach-

ing 0% in 2015. Conversely, Indonesia still ranked sixth in Southeast Asia in 2023 as the country with the highest poverty rate. Meanwhile, the Philippines demonstrated a positive trend, with a decline in poverty rates from 10.5% in 2009 to 4.7% in 2018.

Challenges in education and social work also vary across the three countries. In Indonesia, the primary focus lies on curriculum standardization and the development of relevant theoretical models. In Malaysia, social work education is heavily influenced by colonial history, multiculturalism, and professionalism. Meanwhile, in the Philippines, innovations such as "community kitchens" have become a tangible form of social service delivery, particularly during the pandemic.

The data analysis shows that investment plays a key role in driving economic growth in all three countries. High levels of investment in the past have been shown to create a sustainable cycle of growth for the current period. However, the study also warns that unequal increases in investment can have negative social impacts, such as declining school enrollment or increasing poverty if wealth distribution is not managed effectively.

The relationship between labor force participation and poverty is strong in this region. High participation rates typically help reduce poverty by providing direct income to the community. However, challenges arise if unemployment remains high despite increased participation. Therefore, investment in education and skills training is key in all three countries to ensure the workforce is absorbed by available jobs.

The dynamics observed in this model likely reflect general regional trends in Southeast Asia, where investment is a key driver of economic growth but does not always translate into immediate improvements in social indicators. The Panel Vector Autoregression (PVAR) model used combines data from Indonesia, Malaysia, and the Philippines to capture interactions between similar variables across the region, such as how past investments create a sustainable growth cycle for current investments at the regional level.

The model also reveals that regionally, there is a risk of negative social impacts from investments if not managed well, such as declining school enrollment or increasing poverty due to unequal wealth distribution. Although statistically, these data are considered "stationary" and

represent a common trend, the absence of long-run relationships (cointegration) suggests that each country has unique domestic factors that can disrupt the model's predictive chain over very long time horizons.

CONCLUSION

A rise in "Investment" during the preceding time has a noteworthy effect on "Investment" during the present period, resulting in an ongoing cycle of expansion. Nonetheless, a rise in "Investment" over the preceding time frame can have a detrimental effect on "School Enrollment," "Poverty," and "Labor Force Participation." This demonstrates that investments may have a big social impact in addition to stimulating economic growth. If wealth is distributed more unequally, there may be fewer people working, more people living in poverty, and fewer people attending school as a result of increased investment. Furthermore, this study demonstrates that variations in "school enrollment," "poverty," and "labor force participation" from the prior era also have an impact on each of the other variables in current period. Although the model employed in this study does a good job of explaining fluctuations in the data, the Unrestricted Cointegration Rank Test (Trace) findings indicate that the model's variables do not exhibit a long-term link. This suggests that long-term changes may not be accurately predicted by these models. It is evident from the IRF results that modifications to one variable will affect that variable as well as other variables in the next period, but the impact will decrease over time. This shows the importance of considering the long-term impacts of investment decisions and other economic policies. Overall, this research provides valuable insight into how investment and other economic variables influence each other. While investment can drive economic growth, this research shows that it can also have a significant social impact. As a result, it's critical that investors and politicians think through the long-term effects of their choices and strive for a balance between social welfare and economic progress.

However, despite the fact that investment is a fundamental factor contributing to the economic growth of Indonesia, Malaysia, and the Philippines, such growth is not an automatic response to social issues. Although economic growth creates a sustainable process for itself, it may adversely affect the enrollment rate in

schools and poverty in the short run, especially when the wealth generated is not distributed equally among the population. Such results support the existence of a "growth paradox," in which economic growth produces negative effects, including the creation of more economic pressures that force children at school age to join the labor force.

This implies that the government has to strike a balance between economic development and social policy through the provision of investments that promote the well-being of society. Investments should be made in labor-intensive industries along with the provision of social security in order to alleviate poverty. In addition, investment in human resources is also essential through education and training in order to ensure that development does not come at the expense of education. Standardization of social interventions is also important at the regional level in order to deal with problems such as inequality and mental illnesses due to uneven development.

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Annex. Impulse Response Function (IRF)

Response Of Investment:				
Period	Investment	Labor Force Participatio	Poverty	School Enrollment
1	0.728113	0.000000	0.000000	0.000000
	(0.05945)	(0.00000)	(0.00000)	(0.00000)
2	0.674702	-0.111207	-0.090785	-0.020904
	(0.10543)	(0.10229)	(0.08961)	(0.08418)
3	0.568710	-0.152649	-0.098212	0.010062
	(0.11266)	(0.10706)	(0.08515)	(0.10352)
4	0.477270	-0.157622	-0.101045	0.046834
	(0.12206)	(0.10230)	(0.07504)	(0.11855)
5	0.403415	-0.156542	-0.102123	0.076537
	(0.13312)	(0.09966)	(0.06766)	(0.14028)
6	0.346073	-0.155658	-0.102232	0.097196
	(0.14106)	(0.10345)	(0.06347)	(0.16239)
7	0.302254	-0.156575	-0.101726	0.109844
	(0.14512)	(0.11127)	(0.06168)	(0.18066)
8	0.268940	-0.159297	-0.100799	0.116188
	(0.14639)	(0.12009)	(0.06137)	(0.19435)
9	0.243590	-0.163395	-0.099570	0.117843
	(0.14623)	(0.12845)	(0.06193)	(0.20418)
10	0.224205	-0.168393	-0.098119	0.116135
	(0.14569)	(0.13597)	(0.06297)	(0.21116)
Response Of Labor Force Participatio:				
Period	Investment	Labor Force Participatio	Poverty	School Enrollment
1	-0.076346	0.958791	0.000000	0.000000
	(0.11089)	(0.07828)	(0.00000)	(0.00000)
2	-0.156507	0.878740	0.042835	0.026366
	(0.15525)	(0.15197)	(0.11801)	(0.11119)
3	-0.193734	0.864097	0.030703	0.060581
	(0.16556)	(0.15468)	(0.11007)	(0.13522)
4	-0.224253	0.847499	0.018530	0.090891
	(0.18685)	(0.15964)	(0.11047)	(0.16400)
5	-0.244943	0.831266	0.007149	0.115278
	(0.21105)	(0.16666)	(0.11217)	(0.20181)
6	-0.257245	0.813507	-0.003660	0.133772
	(0.23333)	(0.17861)	(0.11475)	(0.24272)

Response Of Labor Force Participatio:					
Period	Investment	Labor Participatio	Force	Poverty	School Enrollment
7	-0.262915	0.793967		-0.014035	0.147291
	(0.25226)	(0.19451)		(0.11774)	(0.28254)
8	-0.263537	0.772875		-0.024058	0.156853
	(0.26787)	(0.21270)		(0.12099)	(0.31950)
9	-0.260396	0.750562		-0.033784	0.163345
	(0.28064)	(0.23191)		(0.12444)	(0.35297)
10	-0.254484	0.727337		-0.043248	0.167478
	(0.29114)	(0.25131)		(0.12810)	(0.38279)
Response Of Poverty:					
Period	Investment	Labor Participatio	Force	Poverty	School Enrollment
1	0.183326	0.503500		1.517744	0.000000
	(0.18525)	(0.18001)		(0.12392)	(0.00000)
2	0.134769	0.546094		1.502903	-0.049824
	(0.26900)	(0.28688)		(0.23245)	(0.18609)
3	-0.030040	0.554276		1.516238	-0.019932
	(0.29686)	(0.30342)		(0.23263)	(0.23792)
4	-0.186686	0.620884		1.533076	0.031338
	(0.33991)	(0.31738)		(0.23565)	(0.29090)
5	-0.323570	0.700999		1.551794	0.078938
	(0.39177)	(0.33740)		(0.24481)	(0.36274)
6	-0.439387	0.782341		1.571297	0.116930
	(0.44362)	(0.36748)		(0.25751)	(0.44340)
7	-0.537059	0.861203		1.591040	0.145393
	(0.49315)	(0.40557)		(0.27222)	(0.52607)
8	-0.620198	0.936956		1.610740	0.166081
	(0.54051)	(0.44906)		(0.28817)	(0.60835)
9	-0.692030	1.009918		1.630232	0.180922
	(0.58643)	(0.49630)		(0.30503)	(0.68970)
10	-0.755156	1.080610		1.649413	0.191570
	(0.63153)	(0.54641)		(0.32270)	(0.77008)
Response Of School Enrollment:					
Period	Investment	Labor Participatio	Force	Poverty	School Enrollment
1	-0.405932	0.240438		0.105820	1.467428
	(0.17530)	(0.17101)		(0.16966)	(0.11982)

Period	Response Of School Enrollment:				School Enrollment
	Investment	Labor Participatio	Force	Poverty	
2	-0.533682	0.950287		-0.001386	1.796384
	(0.30346)	(0.30866)		(0.28091)	(0.23110)
3	-0.496949	1.076690		0.024453	1.774364
	(0.37366)	(0.37885)		(0.32869)	(0.32230)
4	-0.385406	1.052614		0.040742	1.646125
	(0.41597)	(0.39391)		(0.32442)	(0.38329)
5	-0.273165	0.974297		0.051494	1.497400
	(0.45696)	(0.38949)		(0.30429)	(0.45161)
6	-0.179194	0.885105		0.059618	1.357002
	(0.49321)	(0.39046)		(0.28349)	(0.52990)
7	-0.106013	0.799541		0.066401	1.232271
	(0.51880)	(0.40482)		(0.26693)	(0.60524)
8	-0.051055	0.721723		0.072432	1.123320
	(0.53288)	(0.42874)		(0.25523)	(0.66907)
9	-0.010733	0.652149		0.078006	1.028183
	(0.53776)	(0.45624)		(0.24767)	(0.71897)
10	0.018257	0.590186		0.083287	0.944597
	(0.53659)	(0.48332)		(0.24332)	(0.75569)