Research Paper

The Effectiveness of Government Policies in Reducing Poverty and Income Inequality in Indonesia: An Empirical Study Using the PSM Method

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Abstract
Despite economic growth, Indonesia faces ongoing poverty and inequality issues. Social assistance programs have been implemented, but there is limited evidence of their long-term effectiveness. This study assesses the impact of these programs on four household outcomes related to sustainable income: Training Accessibility, SMSE Accessibility, Information Accessibility, and Financial Inclusion. Using propensity score matching with the SUSENAS 2022 data, the research estimates the effects through logistic regression based on pre-treatment factors, including demographics, assets, and infrastructure. Kernel matching calculates the Average Treatment Effect on the Treated (ATT), tested across urban and rural groups. Findings indicate a positive relationship between social programs and SMSE Accessibility (ATT = +0.025, $p < 0.01$), thereby enhancing small enterprise and market access. No effects are found on Training and Information Accessibility, indicating pre-existing differences rather than program impacts. Surprisingly, a negative effect is observed for Financial Inclusion (ATT = -0.053, $p < 0.01$), where treated households exhibit lower formal financial inclusion, suggesting that further investigation is warranted. These findings offer critical insights for policymakers: while current social assistance programs effectively enhance micro-enterprise development, they should be complemented with targeted financial literacy initiatives and improved access to formal banking services to maximize long-term poverty reduction and economic empowerment outcomes.

Keywords *Income Inequality, Poverty, Propensity Score Matching*

INTRODUCTION

Despite experiencing strong economic growth, Indonesia continues to face persistent poverty and inequality. These issues are driven by socio-economic factors, such as unemployment, inflation, and income distribution, which interact in complex ways to influence poverty. Growth alone has not solved disparities, requiring targeted education, healthcare, and social programs for inclusive growth. Growth has not significantly reduced income inequality, as benefits are unevenly shared (Mkrtchyan et al., 2025). Fiscal policies, especially in education and health, can directly reduce poverty, but have a limited impact on inequality (Agussalim et al., 2024). From 2013 to 2019, Indonesia's poverty rate steadily declined, with BPS reporting a decrease from 9.82% in March 2018 to 9.41% in March 2019. However, in 2020, COVID-19 led to a sharp rise in poverty, affecting 26.42 million people. By March 2024, the rate dropped to 9.03%, indicating economic recovery and the success of the National Economic Recovery (PEN) program.

Several studies indicate that Indonesia has experienced mixed success in reducing poverty and inequality through policies such as the Family Hope Program and regional initiatives, while facing challenges including data inaccuracies and regional disparities (Simamora & Tanjung, 2025). Globally, countries such as India, Ghana, and Iran have made progress in gender equality and health through empowerment and social transfers, but still struggle with higher education and resource coordination (Roshandel et al., 2019; Wolff, 2024). Causal policy evaluation faces issues like endogeneity, selection bias, and measurement errors, though methods such as IV, DiD, EXCEL, and copula models are used; PSM, in particular, effectively assesses policies like Rastra-BPNT, Raskin,

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PKH, and JKN, showing positive impacts on food expenditure, poverty reduction, and health access (Tohari et al., 2019).

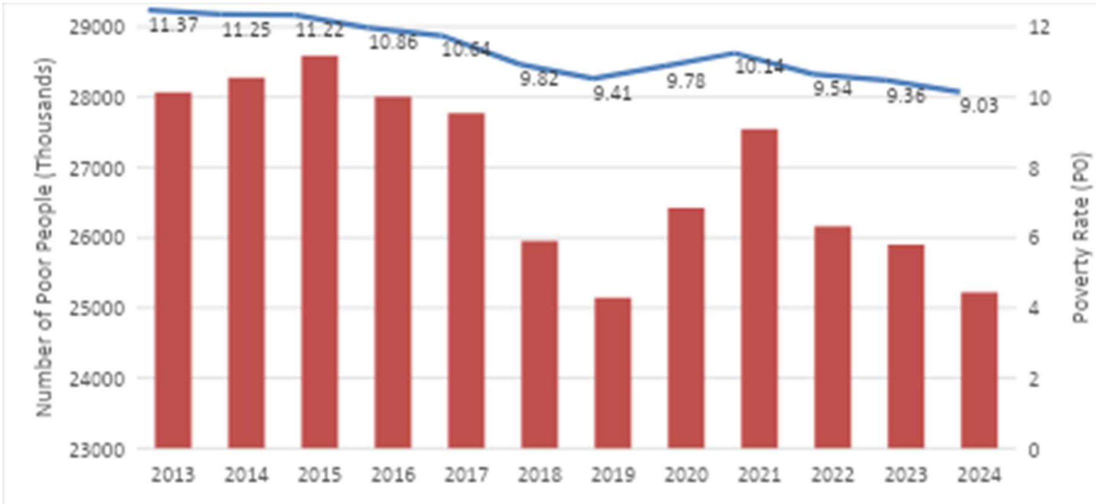


Figure 1. Poverty Rate in Indonesia, 2013 – 2024

A key gap exists in understanding how social assistance programs influence long-term income-generating capacities beyond immediate needs. While most research focuses on short-term outcomes, such as food security and health, there is limited empirical evidence on whether these programs promote long-term economic empowerment through training, micro-enterprise access, market information, and financial services, crucial for breaking the cycle of intergenerational poverty. This study examines the impact of Indonesia's social assistance on four key dimensions of livelihood: training, access to SMSE, information, and financial inclusion. Using propensity score matching with SUSENAS 2022 data, it estimates effects while controlling for household characteristics, assets, and infrastructure. The goal is to identify which pathways to economic self-sufficiency are effective and where policy support is needed for lasting poverty reduction outcomes.

LITERATURE REVIEW

Policies targeting poverty and inequality focus on improving living conditions for disadvantaged groups by reducing income disparities and expanding access to essential services, such as health, education, and social welfare (Saputra, 2024). Conditional Cash Transfers (CCTs), such as Indonesia's *Program Keluarga Harapan* (PKH), are key tools in this effort, offering direct financial support under conditions like school attendance and health check-ups, to break the poverty cycle and enhance long-term opportunities (Sanchez & Yulee, 2022). While PKH increases consumption and reduces poverty, benefits are uneven, especially among the poorest, and it does not significantly lower child labor, partly due to targeting issues and behavioral distortions caused by transfer amounts (Nuryadin et al., 2023).

Numerous studies, both in Indonesia and internationally, utilize Propensity Score Matching (PSM) to evaluate social assistance programs. For instance, Nuryadin et al. (2023) found that the Program Keluarga Harapan (PKH) positively impacted household consumption and poverty reduction in Yogyakarta, employing PSM to assess effectiveness—an approach aligned with current research. Similarly, Ramos et al. (2021) used PSM to evaluate Brazil's Bolsa Família Program (BFP), showing reductions in child mortality and leprosy incidence. Although some studies note heterogeneity in program impacts (Millán et al., 2019), few explore underlying factors such as regional disparities and household characteristics—an area this study aims to address by analyzing how different subgroups respond to the CCT and how program features influence its effectiveness in reducing poverty. This study distinguishes itself by shifting focus from short-term welfare effects to sustainable income-generating capacities, examining four interconnected dimensions—Training Accessibility, SMSE Accessibility, Information Accessibility, and Financial Inclusion—that represent pathways to economic self-sufficiency. Unlike studies evaluating single programs, this research assesses Indonesia's comprehensive social assistance ecosystem, which incorporates urban-rural stratification, explicitly addressing the heterogeneity gap and providing policymakers with actionable insights on which capability-building mechanisms require strengthening for long-term poverty alleviation.

RESEARCH METHOD

This study examines the impact of program participation on four household outcomes, training accessibility, SMSe accessibility, information accessibility, and financial inclusion using propensity score matching (PSM) to create a control group from the SUSENAS 2022 sample. SUSENAS 2022 is chosen because it provides recent, comprehensive national household data reflecting post-pandemic conditions, with complete treatment and outcome information, and a large sample size (~300,000 households) for urban-rural analysis. PSM matches treated households with similar controls based on predicted participation probabilities using pre-treatment covariates (Rosenbaum & Rubin, 1983).

Formally, the estimand of interest is the Average Treatment effect on the Treated (ATT):

$$ATT = E[Yi(1) \mid M_i = 1] - E[Yi(0) \mid M_i = 1]$$

where $M_i = 1$ indicates household i is a program participant (treatment), $M_i = 0$ otherwise; $Yi(1)$ dan $Yi(0)$denote the potential outcomes with and without treatment, respectively (Trujillo et al., 2017). Under the conditional independence assumption (CIA) and overlap, matching on the propensity score yields an unbiased estimator of the ATT.

The propensity score is estimated in the pooled sample (treated + control) via a logistic regression:

$$pX_i = Pr\ X_i \ = \Lambda X_i = 1 + exp\ X_i\ exp(X_i)$$

where Xi is a vector of pre-treatment household- and location-level covariates (demographics, socio-economic status, baseline asset ownership, urban/rural indicator, household head education, household size, baseline employment/income proxies, and local infrastructure proxies). Choice of covariates follows the "selection-on-observables" principle: include all variables that plausibly affect both program participation and outcomes (Khandker et al., 2010; Caliendo & Kopeinig, 2005).

Table 1. Operational definition of variables

Variable (label)	Operational definition	Measurement/coding
Treatment (M)	Household is a beneficiary of the social assistance program.	Binary: 1 = reported receipt of program in reference period; 0 = otherwise
Training_Accessibility (TRAIN_ACC)	Household reports at least one member who received or accessed vocational, business, or	Binary: 1 = yes; 0 = no. Alternatively, an index (count of training types)

Variable (label)	Operational definition	Measurement/coding
	training in the last 12 months.	
SMSE_Accessibility (SMSE_ACC)	Household or member owns or reports access to MSME services.	Binary or index: 1 = access/ownership; 0 = none. If continuous: number of MSME-related services accessible.
Information_Accessibility (INFO_ACC)	Household reports access to market/info channels via mobile.	Binary/index: 1 = uses relevant information channels; 0 = otherwise. Could be a composite index (0–1)
Financial_Inclusion (FINCL)	Household has at least one member with a bank or formal credit in the past 12 months.	Binary: 1 = has/formal account or loan; 0 = none. Alternatively, build an index including savings, checking, credit, and insurance.
sex	Sex of the household head	Binary: 1 = Male, 0 = Female
marstat	Marital status of household head	Categorical: 1 = Single, 2 = Married/cohabiting, 3 = Divorced/separated, 4 = Widowed (or dichotomize: 1 = Married, 0 = Not married)
yos	Household head's years of schooling	Continuous integer: years of schooling OR ordinal categories
Balita	Number of children under five years in the household	Integer count. Also create binary indicator Balita_bin = 1 if ≥1 child under five
HHAge	Age of household head	Continuous (years). Consider grouping for heterogeneity
HHSize	Number of usual residents	Integer.
HHsizeSquare	Square of household size.	Computed variable: HHSize^2 (continuous)
ListrikKWH	Monthly household electricity consumption (kWh)	Continuous (kWh per month). If SUSENAS reports expenditure, convert the rupiah using the local tariff or use the binary electricity access indicator if consumption is unavailable.
BBMLiter	Household monthly fuel consumption (liters) — usually vehicle fuel	Continuous (liters/month). If only expenditure is available, use rupiah-to-liter conversion with documented

Variable (label)	Operational definition	Measurement/coding
	(BBM) or overall household fuel	prices; alternatively, separate FuelTransport vs FuelCooking
lahan_kap	Household-owned agricultural land area (converted to hectares)	Continuous (hectares). If original in m^2 or "kap" units, convert to hectares: ha = units × conversion
Minumtidaklayak	Unsafe/unimproved drinking water source for the household	Binary: 1 = unimproved/unprotected drinking water source, 0 = improved source
AssetDwelling	Dwelling-asset index: measure of housing quality & assets	Continuous index (z-score) created via PCA on indicators like floor and wall materials, ownership of TV, fridge, motorcycle, bicycle, refrigerator, mobile phone, and dwelling tenure.
ChronicHealth	Presence of at least one household member with a chronic condition	Binary: 1 = at least one member reports chronic illness; 0 = none
InsuranceAccess	Household access to formal health insurance.	Binary: 1 = at least one member covered by formal health insurance, 0 = none. Optionally: proportion of household members insured (0–1)

FINDINGS AND DISCUSSION

This chapter estimates the probability of PKH participation using logit and probit models to differentiate between treated (PKH recipients) and control groups based on characteristics such as household size, education, infrastructure, and location. The logit model uses log-odds, while the probit model relies on the normal distribution, providing propensity scores (P^i). Comparing models ensures good overlap for matching. Kernel matching then assigns weights to controls based on their proximity to treated units using a Gaussian kernel, thereby enhancing efficiency and reducing variance. Cross-validation selects the bandwidth (h) to balance bias and variance, and the ATT is the mean outcome difference such as, economic opportunity between recipients and matched controls.

Table 2. Estimation results

Variables	Coefficient	Standard Error	Coefficient (Urban)	Standard Error (Urban)	Coefficient (Rural)	Standard Error (Rural)
sex	-0.015	0.009	-0.038***	0.017	-0.006	0.011
marstat	-0.157***	0.015	-0.163***	0.028	-0.163***	0.018
yos	0.000	0.001	-0.005***	0.002	0.004***	0.001
Balita	-0.365***	0.009	-0.435***	0.018	-0.346***	0.011
HHAge	0.000	0.000	0.002***	0.001	0.000	0.000
HHSize	0.472***	0.012	0.481***	0.023	0.471***	0.014

HHsizeSquare	-0.018***	0.001	-0.020***	0.002	-0.018***	0.001
ListrikKWH	-0.003***	0.000	-0.003***	0.000	-0.003***	0.000
BBMLiter	-0.006***	0.000	-0.007***	0.001	-0.005***	0.000
lahan_kap	-0.016***	0.001	-0.020***	0.001	-0.014***	0.001
Minumtidaklayak	0.176***	0.016	0.254***	0.047	0.128***	0.017
AssetDwelling	-0.076***	0.001	-0.079***	0.001	-0.071***	0.001
Chronic Health	0.225***	0.013	0.254***	0.024	0.204***	0.015
Insurance Access	-0.417***	0.166	-0.791***	0.308	-0.161	0.203
Cons	-1.721***	0.040	-1.752***	0.076	-1.769***	0.047
Observation			**129,123**		**197,653**	
Log Likelihood			**- 44,528.66**		**- 103,146.69**	
Pseudo R-Square			**0.1749**		**0.1013**	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

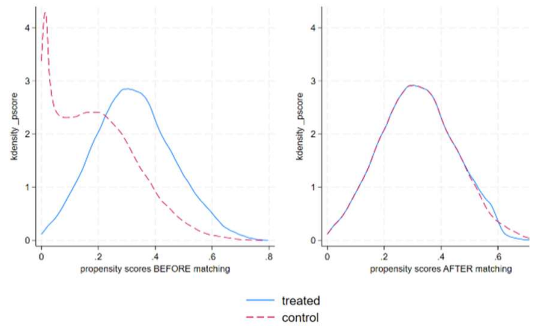
The analysis highlights factors influencing social assistance in Indonesia, including household demographics, assets, and access to services, which are connected to program participation. Urban areas exhibit higher targeting accuracy due to more pronounced socioeconomic differences, with larger households being more likely to qualify; however, benefits tend to decrease with increasing household size. Households with young children are less likely to qualify, indicating a mismatch with actual vulnerabilities. Socioeconomic indicators, such as electricity use, fuel consumption, and assets, reflect welfare, with higher consumption being linked to lower participation. Urban education correlates negatively with receipt, as better labor market returns reduce eligibility.

In contrast, in rural areas, education indicates aspirations without improved welfare outcomes (Yang, 2017). Access to health insurance in urban areas tends to favor wealthier households, acting as a negative welfare indicator, with vulnerability indicators like health issues also playing a role. Asset and consumption proxies are strong predictors, contrasting with Latin American programs that emphasize child dependency (Fiszbein & Schady, 2009). The differing signs between health vulnerabilities and insurance underscore challenges in targeting health equity (Anindya et al., 2020).

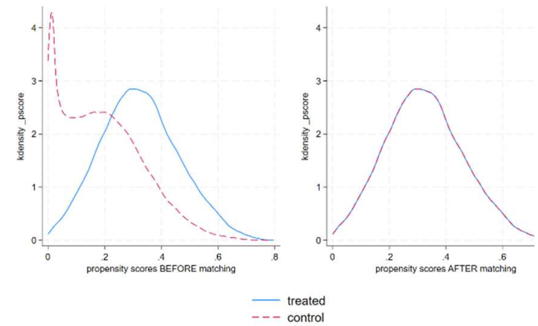
Table 3. Robustness Test

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.139	47707.59	0	23.3	12.3	88.6*	0.21*	100
Matched	0	11.99	0.607	0.2	0.1	1.8	1.17	100

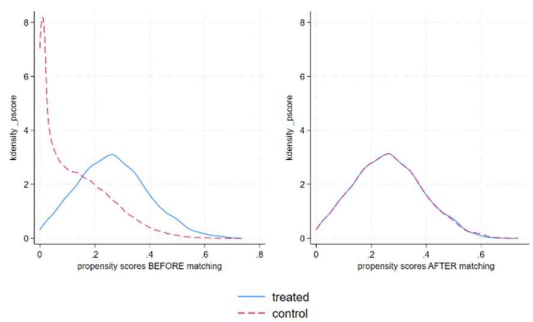
The propensity-score model helps create a credible comparison group. Before matching, covariates predicted program receipt with a pseudo-R^2 of 0.139 and a significant LR χ^2, and the standardized mean bias was high (~23.3%), indicating imbalances and confounding. After one-to-one matching, diagnostics improved: pseudo-R2 neared zero, the LR test was not significant ($\chi 2=11.99$, p=.607), biases dropped to ~0.2%, Rubin's BBB stat decreased from 88.6 to 1.8, and the variance ratio became acceptable (~1.17). These results demonstrate that matching eliminated the relationship between observables and treatment, achieving excellent covariate balance —a key goal of propensity-score matching (Rosenbaum & Rubin, 1983).



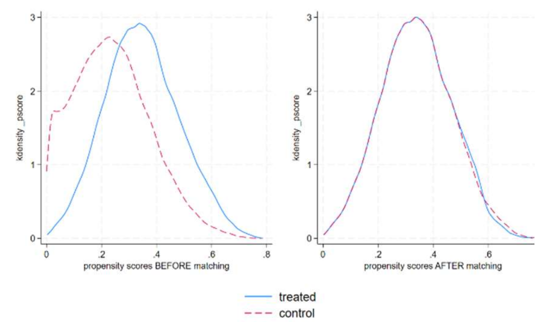
Main Matching



Robustness Test



Urban



Rural

Figure 2. Density Plots

Density plots compare propensity-score distributions for treated (solid blue) and control (dashed red) groups, before and after matching. Matching increases overlap, thereby improving covariate balance and supporting the un-confoundedness of the ATT. Minor residual tail differences suggest caution with extreme scores. Additional diagnostics are advised before reporting causal results estimates.

Table 4. Estimation Results

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Training_Accesibility	Unmatched	0.003	0.0036	-0.0010	0.000	-4.22
	ATT	0.003	0.0028	-0.0002	0.000	-0.78
Financial_Inclusion	Unmatched	0.864	0.8312	0.0328	0.002	21.1
	ATT	0.863	0.9159	-0.0533	0.002	-31.94
SMSE_Accesibility	Unmatched	0.092	0.0538	0.0382	0.001	37.56
	ATT	0.092	0.0663	0.0252	0.001	17.56
Information_Accesibility	Unmatched	0.592	0.6738	-0.0819	0.002	-40.93
	ATT	0.595	0.5922	0.0024	0.003	0.92
Robustness Test Rigid Neigbor						
Training_Accesibility	Unmatched	0.0026	0.0036	-0.001	0.000	-4.22
	ATT	0.0026	0.0027	0.000	0.000	-0.36
Financial_Inclusion	Unmatched	0.8639	0.8312	0.033	0.002	21.1
	ATT	0.8639	0.9162	-0.052	0.002	-29.8

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
SMSE_Accesibility	Unmatched	0.0920	0.0538	0.038	0.001	37.56
	ATT	0.0920	0.0660	0.026	0.001	17.66
Information_Accesibility	Unmatched	0.5918	0.6738	-0.082	0.002	-40.93
	ATT	0.5918	0.5892	0.003	0.003	0.98
		Urban				
Training_Accesibility	Unmatched	0.0021	0.0035	-0.0015	0.0005	-3.25
	ATT	0.0021	0.0026	-0.0005	0.0005	-1.07
Financial_Inclusion	Unmatched	0.8356	0.7849	0.0507	0.0032	15.93
	ATT	0.8351	0.8974	-0.0623	0.0035	-17.85
SMSE_Accesibility	Unmatched	0.1001	0.0511	0.0490	0.0018	26.70
	ATT	0.1002	0.0725	0.0277	0.0029	9.59
Information_Accesibility	Unmatched	0.6966	0.7759	-0.0793	0.0033	-23.83
	ATT	0.6982	0.6905	0.0076	0.0047	1.61
		Rural				
Training_Accesibility	Unmatched	0.0027	0.0037	-0.0009	0.0003	-3.07
	ATT	0.0028	0.0034	-0.0006	0.0003	-1.8
Financial_Inclusion	Unmatched	0.8741	0.8663	0.0078	0.0017	4.53
	ATT	0.8727	0.9226	-0.0499	0.0019	-26.48
SMSE_Accesibility	Unmatched	0.0891	0.0558	0.0333	0.0012	26.65
	ATT	0.0886	0.0630	0.0256	0.0016	15.53
Information_Accesibility	Unmatched	0.5542	0.5961	-0.0420	0.0025	-16.78
	ATT	0.5566	0.5504	0.0062	0.0031	2.01

After propensity-score matching, the program's positive impact on SMSE accessibility decreases from +0.038 to +0.025. However, it remains significant (SE = 0.001, $p < 0.01$), indicating that social assistance effectively reduces market access barriers rather than building formal skills. Imbalances in training and information access are eliminated, indicating they stem from pretreatment covariates. Interestingly, the financial-inclusion gap reverses post-matching: treated units have higher unconditional inclusion, but matched controls show higher inclusion (ATT ≈ −0.053, $p<0.01$). This paradox suggests that behavioral barriers, such as cognitive costs resulting from financial scarcity (Mani et al., 2013) and institutional distrust alongside structural obstacles like documentation requirements and geographic distance, disproportionately affect beneficiaries (Demirgüç-Kunt et al., 2018). Cash transfers may also serve as a substitute for formal credit, thereby reducing the need for banking services. Sensitivity analyses are needed before confirming a causal reduction. The pattern of unchanged training access but improved managerial/SME access aligns with prior research showing modest returns to short training and greater gains when programs target market access (McKenzie & Woodruff, 2012), extending this literature by demonstrating that capability-building occurs through learning-by-doing in markets is a critical insight for designing complementary policies that integrate financial literacy and trust-building alongside transfers.

CONCLUSIONS

This study assesses Indonesia's social assistance outcomes related to sustainable income, including Training, SMSE, Information Accessibility, and Financial Inclusion. Using propensity-score matching, we find a positive impact on SMSE Accessibility (ATT = +0.025, $p < 0.01$), indicating that the program effectively strengthens market linkages for microenterprises. Differences in Training and Information Accessibility are negligible post-matching. At the same time, the reversed

Financial Inclusion gap, where treated households show lower formal financial engagement (ATT = -0.053, p<0.01), raises concerns about unintended behavioral and institutional barriers. These findings yield specific policy implications. First, policymakers should scale market integration components by establishing SME clusters, facilitating supply-chain connections, and providing dedicated market access support rather than generic training programs. Second, the financial inclusion paradox necessitates redesigning interventions: integrating mandatory financial literacy modules within cash transfer programs, partnering with mobile banking providers to reduce geographic barriers, simplifying documentation requirements for beneficiaries, and establishing trust-building mechanisms such as community financial agents. Third, training programs should shift from classroom-based skill development to practical, market-embedded learning such as apprenticeships with successful SME operators and on-the-job mentoring programs.

LIMITATIONS & FURTHER RESEARCH

Limitations include propensity-score matching only adjusting for observable factors; future research should employ sensitivity analyses, doubly robust estimators, IPTW, and experimental or IV approaches, especially for financial inclusion mechanisms.

REFERENCES

Agussalim, A., Nursini, N., Suhab, S., Kurniawan, R., Samir, S., & Tawakkal, T. (2024). The path to poverty reduction: How do economic growth and fiscal policy influence poverty through inequality in Indonesia? *Economies, 12*(12). https://doi.org/10.3390/economies12120316

Anindya, K., Lee, J. T., McPake, B., Wilopo, S. A., Millett, C., & Carvalho, N. (2020). Impact of Indonesia's national health insurance scheme on inequality in access to maternal health services: A propensity score matched analysis. *Journal of Global Health, 10*(1). https://doi.org/10.7189/JOGH.10.010429

Caliendo, M., & Kopeinig, S. (2005). *Some practical guidance for the implementation of propensity score matching.*

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution.*

Fiszbein, A., & Schady, N. (2009). *Reducing present and future poverty.*

Khandker, S. R., Koolwal, G. B., & Samad, H. A. (2010). *Handbook on impact evaluation.*

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *Science, 341*(6149), 976–980.*

Mckenzie, D., & Woodruff, C. (2012). *What are we learning from business training and entrepreneurship evaluations around the developing world?*

Millán, T. M., Barham, T., Macours, K., Maluccio, J. A., & Stampini, M. (2019). Long-term impacts of conditional cash transfers: Review of the evidence. *World Bank Research Observer, 34*(1), 119–159. https://doi.org/10.1093/wbro/lky005

Mkrtchyan, T., Khachatryan, A., & Ratner, S. (2025). Measuring inclusive growth in developing countries: Composite index approach and sectoral transformation analysis. *Journal of Risk and Financial Management, 18*(6). https://doi.org/10.3390/jrfm18060336

Nuryadin, D., Darpito, H., Astyka, G., And, R., Bagus, I., & Cesario, P. (2023). Examining the efficacy of conditional cash transfer programs in reducing poverty in Yogyakarta, Indonesia. *Journal of Economic Development, 48*(4), 141–153.*

Ramos, D., da Silva, N. B., Ichihara, M. Y., Fiaccone, R. L., Almeida, D., Sena, S., Rebouças, P., Pinto, E. P., Paixão, E. S., Ali, S., Rodrigues, L. C., & Barreto, M. L. (2021). Conditional cash transfer program and child mortality: A cross-sectional analysis nested within the 100 Million Brazilian Cohort. *PLoS Medicine, 18*(9). https://doi.org/10.1371/journal.pmed.1003509

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Roshandel, J., Sadeghi, F., & Tadrisi, S. (2019). Gender equality and empowerment in Iran: A comparison between Ahmadinejad's and Rouhani's governments. *Journal of South Asian and Middle Eastern Studies, 42*(3), 35–53. https://doi.org/10.33428/jsoutasiamiddeas.42.3.0035

Sanchez, D., & Yulee, P. (2022). *Show me the money! The effects of a conditional cash transfer program on the labor market in Ecuador.*

Saputra, G. R. (2024). Analyzing the impact of government policy on poverty alleviation: Evaluating social protection programs, healthcare access, and economic reforms. *Inspirasi & Strategi (INSPIRAT): Jurnal Kebijakan Publik & Bisnis, 15*(1), 27–36.

Simamora, P., & Tanjung, M. (2025). The role of the Family Hope Program (PKH) in improving the social welfare of the Muslim community in Pematangsiantar City. *Social Economics and Technology, 6*(1), 1014–1020. https://doi.org/10.33122/ejeset.v6i1.536

Tohari, A., Parsons, C., & Rammohan, A. (2019). Targeting poverty under complementarities: Evidence from Indonesia's unified targeting system. *Journal of Development Economics, 140*, 127–144. https://doi.org/10.1016/j.jdeveco.2019.06.002

Wolff, G. (2024). Promoting gender equality through localized development strategies: Leveraging identification. *Journal of International Humanitarian Action, 9*(1). https://doi.org/10.1186/s41018-024-00156-7

Yang, Y. (2017). A research on the difference of education returns between urban and rural areas. *Open Journal of Social Sciences, 5*(4), 59–67. https://doi.org/10.4236/jss.2017.54006