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Social assistance performance on local economic development: evidence from island regions in East Indonesia

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Abstract: During economic uncertainty following the COVID-19 pandemic, social assistance is vital for alleviating the economic burden on the poor and vulnerable to poverty, particularly those residing in island-based areas. The research aims to measure the performance of social assistance programs in the regional economy of the North Maluku Archipelago Province. The study employs Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to measure efficiency values, with input variables including social aid, unemployment, and inflation, while the output variable is poverty. The results reveal that social assistance is ineffective in reducing poverty. Several obstacles, including the minimal budget allocation, inaccuracies in identifying assistance recipients, and insufficient time for aid distribution are identified as primary causes of the inefficiency of social aid programs. Updating poverty data into one unified and integrated dataset is essential for the efficiency distribution of social assistance. Accurate targeting and timely distribution are the keys to the effectiveness of social assistance programs in reducing poverty.

Keywords: Social Assistance; Efficiency; DEA; Stochastic Frontier
JEL Classification: H53; H55; H71; I38

Introduction

Social assistance programs play a crucial role in alleviating poverty within local economic development. Social assistance seeks to provide cash and other benefits to compensate for income deficiencies, barriers to accessing healthcare, lack of family support, and conditions of poverty resulting from social vulnerabilities (Baylan, 2019). This addresses the risks encountered by individuals, families, and communities, which may stem from inherent, enduring characteristics and external factors such as natural disasters, economic recessions, or social conflicts (Indonesian Ministry of National Development Planning, 2014). Therefore, allocating a budget for social aid is instrumental in fulfilling people's basic needs.

Previous studies have explored the impact of social assistance on macroeconomic variables such as poverty and inequality. For instance, increasing social compensation payments in rural areas has been linked to poverty reduction (Le-rong & Xiao yun, 2021). Social assistance programs are designed to aid poor and marginalized individuals in meeting their basic needs within the community. Other studies have shown that government social assistance programs contribute positively to long-term GDP growth (De Senna & Souza, 2016), and social safety nets significantly reduce chronic poverty (Devereux, 2002).

In Indonesia, initiatives for social protection aimed at combating poverty and inequality include social assistance programs as a vital component. According to Rizki (2021), social program support during the COVID-19 pandemic has had a modest impact on increasing assistance to disadvantaged individuals. The poverty rate in Indonesia declined from 13.33% in 2010 to 9.22% in 2019 before the COVID-19 outbreak, but rose to 9.71% during the pandemic in 2021 (Indonesian Central Bureau of Statistics, 2022). Meanwhile, the budget for social assistance in 2020 amounted to IDR 230.21 trillion. Despite the high effectiveness of the national social assistance policy, such as the Family Hope Program (PKH), in reducing poverty, and the lowest effectiveness value of the non-cash food assistance program (BPNT) for poverty reduction, increasing the social assistance program budget is seen as having a gradual impact on reducing poverty and unemployment rates (Arfandi & Sumiyarti, 2022).

Studying the role of social assistance programs in the socioeconomic life of communities is crucial, particularly given the uncertainty of the global economy following the COVID-19 pandemic. There are concerns that unemployment, inflation, and poverty levels will rise, especially in suburban areas and islands. The efficiency and effectiveness of social assistance programs in alleviating poverty in island-based areas differ from those in land-based regions. Communities residing on small islands, distant from economic and political centers, heavily rely on external financial aid (Briguglio, 1995). The social and economic characteristics of coastal island communities make them vulnerable to various upheavals resulting from social, economic, and environmental changes (Fernandes & Pinho, 2017). Therefore, social assistance programs serve as tools to enhance the socioeconomic well-being of islanders, particularly in eradicating poverty.

Studies investigating the performance of social assistance within the context of regional economic development in archipelagic areas are scarce. Previous research on the effects of social assistance on poverty has predominantly focused on urban, land-based areas. For instance, Zhang (2016) examined social assistance for impoverished children in urban areas of China, emphasizing the need for improved services, particularly in education and social support. Another study demonstrated that in cities with higher poverty rates, conditional cash transfers significantly reduce child mortality in Brazil (Aransiola et al., 2023). Similarly, research in India indicated that 89-94% of farming households benefiting from the COVID-19 social assistance package experienced positive outcomes from direct cash transfers (Varshney et al., 2021). Given the limited examination of social assistance in coastal and inland areas, this study aims to assess the effectiveness of social assistance programs in alleviating poverty in island regions. By employing Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), this research evaluates the efficacy of social aid in enhancing the welfare of local communities. This study contributes to the literature by analyzing the impact of social assistance on local economic development.

Research Method

Definition of Input and Output Variables

The utilization of the DEA approach for assessing regional economic performance remains relatively uncommon. Charnes et al. (1989) conducted a study measuring regional economic performance in Chinese cities. They employed indicators such as the number of industrial workers, labor wages, and investment as input variables, while the value of industrial GDP, taxes, and retail sales results served as output variables. Cooper et al. (1995) delved into the measurement of regional economic performance by comparing SFA and DEA methods. Their study focused on the impact of China's economic reforms on industries such as textiles, chemicals, and steel. They utilized a single output and two inputs, specifically labor and capital, to conduct their analysis.

The selection of indicators for this study was driven by the necessity of evaluating the performance of social assistance programs within the regional economy of North Maluku Province. The chosen output variables include the poverty rate at the district/city level, while the input variables comprise the social assistance budget, unemployment rate, and inflation. The analysis unit, referred to as the Decision-Making Unit (DMU), encompasses all regencies and cities within North Maluku Province. District and city panel data for North Maluku Province spanning from 2015 to 2021 was acquired through documentation obtained from the Central Bureau of Statistics. The study's timeframe is restricted to 2021 due to its focus on social assistance data during the peak period of the COVID-19 pandemic, which occurred in 2020 and 2021. Table 1 provides an overview of the average values of the variables across each unit of analysis.

Table 1 Data Information of Input and Output Variables

Regions	Average (2015 -2021)			
	Output	**Input**		
	Poverty	Social Aid	Unemployment	Inflation
	Percent (%)	Billion ($US)*	Percent (%)	Percent (%)
Tidore Island	5.85	21,690.6	4.47	2.72
Ternate Island	6.97	1,239,810.4	5.92	2.72
South Halmahera	10.83	787,290.6	44.2	2.72
West Halmahera	10.28	582,442.6	33.29	2.72
Central Halmahera	7.1	33,127.1	55.34	2.72
East Halmahera	14.04	85,725.3	4.55	2.72
North Halmahera	8.66	654,354.9	5.65	2.72
Morotai Island	4.62	906,009.1	55.91	2.72
Sula Island	8.89	103,399.2	4.42	2.72
Taliabu	3.82	124,675.5	5.85	2.72

*Currency on December 10, 2023
Source: Indonesian Central Bureau of Statistics, 2022

DEA and Stochastic Frontier Models

The DEA models in this study are classified based on whether they are input or output-oriented. Here, the focus is on input orientation, specifically utilizing variables such as social assistance, unemployment, and inflation rates. Additionally, the study employs the parametric frontier stochastic analysis method to evaluate the efficiency performance of social assistance in North Maluku Province. Among the various methods for examining productivity and efficiency, one of the most widely used is the stochastic frontier analysis (SFA) model. Aigner et al. (1977) developed the initial version of this model to quantify the technical efficiency of a business unit or company and identify the sources of technical inefficiency.

Table 2 Summary statistics of Variables

	Output	Inputs		
	Poverty (%)	Social Aid (IDR)	Unemployment (%)	Inflation (%)
Mean	8.10	7.00E+09	4.96	2.72
Standard error	0.36	1.21E+09	0.20	0.12
Median	8.01	3.62E+09	4.72	2.13
Standard deviation	3.04	1.01E+10	1.67	1.03
Kurtosis	2.42	6.77	4.62	1.98
Skewness	0.41	2.08	1.07	0.92
Minimum	3.55	1,000,000	1.94	10.36
Maximum	14.97	4.38E+10	1.9	4.52
Observation	70	70	70	70

The SFA model provides for inefficiency model forms from frontier observations and error or noise variables. Specifically, the stochastic frontier production function equation is as follows.

$$ln(y_{it}) = x_{it}\beta + v_{it} - u_{it} \; i = 1,2,.....,N \; t = 1, 2, ..., T \quad (1)$$

The first thing to do is determine the shape of the model by identifying the research variables, namely the dependent variable and the independent variable. The dependent variable is the poverty rate (y_{it}). The independent variable (x_{it}) is measured by the assumption that these variables impact district/city poverty. By using the double-log specification (Cobb Douglas), the equation function is as follows:

$$ln\ (y_{it}) = \beta_0 + \beta_1 lnX_{1it} + \beta_{2it} lnX_{2it} + \beta_{3it} lnX_{3it} + v_{it} - u_{it} \; i = 1,2,.....,N t = 1, 2, ..., T \quad (2)$$

y_{it} is the output of the district/city $_i$ poverty level, X_{it} is the factor that predicts a production frontier. There are three factors of production input, namely X_1: district social assistance budget; X_2: number of unemployed; X_3: inflation rate. β_0 is the intercept; $_i$ is district/city; t is the time, and β is the parameter to be estimated; $v_{it} - u_{it}$ is the specific error term of i th observation and time t. Amin et al. (2021) noticed the random variable v_{it} is useful for calculating the size of the error and the factors outside the control also called statistical noise in the value of the output variable, along with the combined effects of unspecified input variables in the production function where random normally distributed or N(0, σ^2_v). Meanwhile, the u_i variable is called one-side disturbance which captures the effect of the inefficiency. The research uses the model employed by Battese & Coelli (1992) to estimate the value of technical inefficiency where the variable ui is a non-negative variable ($u_i \geq 0$) and is estimated to be normally truncated N(μ, σ^2) (Battese & Coelli, 1992). Local governments can control the internal error component through regional policies or regulations related to the management of social assistance, as reflected by u_i. This error value has a symmetrical (one-sided) distribution, namely $u_i \geq 0$, where if economic activity is efficient (te = 1,000), then the resulting technical efficiency value is close to its maximum potential, namely $u_i = 0$. Conversely, if $u_i \leq 0$ means below the maximum.

Result and Discussion

Efficiency results of DEA

The DEA model offers two approaches for measuring efficiency scales: DEA-CCR and DEA-BCC. Table 3 presents the estimated efficiency and efficiency scale of social assistance utilization for each district and city in North Maluku Province. The average value of estimated efficiency for DEA-CCR is lower than that for DEA-BCC, at 0.541 and 0.590 respectively, with a maximum efficiency index value of 1.00. Among the 70 periods analyzed, only 5 and 9 were identified as efficient when using the DEA-CCR and DEA-BCC models, respectively. ANOVA testing comparing the efficiency values of DEA-CCR and DEA-BCC yielded an F value of 3.92 at a significant level of 1% and a critical value of 3.49. Additionally, the Spearman test results for the ranking correlation coefficient of efficiency values between DEA-CCR and DEA-BCC analysis indicate a coefficient of 0.93. The positive sign and high Spearman ranking correlation coefficient suggest a very strong relationship in the ranking of each model component. Overall, the efficiency estimates generated by both model techniques exhibit a consistent pattern across regions, as evidenced by the ANOVA and Spearman rank correlation coefficient analyses.

Table 3 Efficiency of Social Security Expenditure, Unemployment, and Inflation

Regions	Year	DEA-CCR	DEA-BCC	Scale Efficiency	Return to Scale
West Halmahera	2015	0.594	0.752	0.79	Decreasing
	2016	0.73	0.73	1	Constant
	2017	0.965	1	0.965	Increasing
	2018	0.722	0.751	0.962	Decreasing
	2019	0.733	0.751	0.976	Decreasing
	2020	0.803	0.805	0.998	Increasing
	2021	0.795	0.795	1	Constant
South Halmahera	2015	0.394	0.678	0.581	Decreasing
	2016	0.672	0.672	1	Constant
	2017	0.653	0.656	0.995	Increasing
	2018	0.623	0.775	0.805	Decreasing
	2019	0.811	0.811	1	Constant
	2020	0.814	0.858	0.949	Decreasing

Table 3 Efficiency of Social Security Expenditure, Unemployment, and Inflation (cont')

Regions	Year	DEA-CCR	DEA-BCC	Scale Efficiency	Return to Scale
	2021	1	1	1	Constant
Central Halmahera	2015	0.544	0.544	1	Constant
	2016	0.527	0.527	1	Constant
	2017	0.326	0.326	1	Constant
	2018	0.543	0.543	1	Constant
	2019	0.575	0.575	1	Constant
	2020	0.565	0.565	1	Constant
	2021	0.457	0.534	0.855	Decreasing
East Halmahera	2015	0.962	0.962	1	Constant
	2016	1	1	1	Constant
	2017	1	1	1	Constant
	2018	1	1	1	Constant
	2019	1	1	1	Constant
	2020	0.977	1	0.977	Decreasing
	2021	0.861	1	0.861	Decreasing
North Halmahera	2015	0.38	0.603	0.631	Decreasing
	2016	0.563	0.563	1	Constant
	2017	0.553	0.556	0.995	Increasing
	2018	0.416	0.576	0.722	Decreasing
	2019	0.605	0.605	1	Constant
	2020	0.574	0.603	0.951	Decreasing
	2021	0.593	0.678	0.874	Decreasing
Sula Islands	2015	0.61	0.646	0.944	Decreasing
	2016	0.652	0.652	1	Constant
	2017	0.625	0.63	0.992	Decreasing
	2018	0.437	0.643	0.679	Decreasing
	2019	0.682	0.682	1	Constant
	2020	0.582	0.629	0.925	Decreasing
	2021	0.688	0.695	0.989	Increasing
Morotai	2015	0.157	0.346	0.454	Decreasing
	2016	0.325	0.325	1	Constant
	2017	0.318	0.319	0.995	Increasing
	2018	0.177	0.312	0.568	Decreasing
	2019	0.334	0.334	1	Constant
	2020	0.289	0.302	0.957	Decreasing
	2021	0.26	0.297	0.874	Decreasing
Taliabu Islands	2015	0.257	0.257	1	Constant
	2016	0.277	0.277	1	Constant
	2017	0.262	0.263	0.996	Increasing
	2018	0.177	0.264	0.671	Decreasing
	2019	0.274	0.274	1	Constant
	2020	0.254	0.267	0.95	Decreasing
	2021	0.237	0.273	0.865	Decreasing
Ternate Island	2015	0.23	0.429	0.536	Decreasing
	2016	0.426	0.426	1	Constant
	2017	0.426	0.429	0.995	Increasing
	2018	0.258	0.452	0.571	Decreasing
	2019	0.499	0.499	1	Constant
	2020	0.534	0.55	0.971	Decreasing
	2021	0.494	0.57	0.865	Decreasing
Tidore Islands	2015	0.288	0.369	0.781	Decreasing
	2016	0.368	0.368	1	Constant
	2017	0.384	0.389	0.987	Decreasing
	2018	0.303	0.417	0.728	Decreasing
	2019	0.429	0.442	0.97	Decreasing
	2020	0.441	0.486	0.906	Decreasing
	2021	0.6	1	0.6	Increasing
Total Average		0.5412	0.5901	0.9093	

Efficiency results of SFA models

The first step in utilizing the Stochastic Frontier Analysis (SFA) model is to check the sign of skewness in the sample data, as suggested by Waldman (1982). This sign is crucial in confirming the appropriateness of the Maximum Likelihood Estimate (MLE). Specifically, a negative skewness sign in the Ordinary Least Squares (OLS) residuals is indicative of a suitable stochastic frontier model (Kumbhakar et al., 2015). In this case, the OLS calculation yields a skewness value of -1.252, confirming that the model aligns with stochastic frontier specifications. Moreover, Coelll (1995) mentions that the feasibility of the stochastic frontier model can also be tested using the Likelihood Ratio (LR) statistical test after estimating the maximum likelihood. This additional test provides further validation of the model's appropriateness for analyzing the data.

Table 4 Frontier production function of regions

Variables parameters (ln Poverty)	OLS	MLE
ln Unemployment	-0.384	-0.319
	(0.012**)	(0.035**)
ln Inflation	0.135	0.068
	(0.343)	(0.635)
ln Social Aid	3.77E-13	-0.061
	(0.935)	(0.629)
Constant	2.484	-
μ	-	0.376
Λ	-	1.935
Σu	-	0.398
Σv	-	0.205
Unrestricted log-likelihood function	-	-29.58
Restricted log-likelihood function	-	-30.25
LR		1.339

Note: **5% significance test, *p-value* in brackets

The equation $-2[L(H_0) - L(H_1)]$ is utilized to compute the statistical likelihood ratio test results. where the restricted (OLS) model's log-likelihood value is $L(H_0)$, and the unrestricted stochastic frontier model's log-likelihood value is $L(H_1)$ (Kumbhakar et al., 2015). The value of likelihood ratio of 1,339 indicates that the finding of rejecting H_0 means there is no technical inefficiency, so the H_1 form can be accepted. The subsequent step involves calculating the technical efficiency expressed as $TE_{it} = \exp(-u_{it})$, following the methodology outlined by Jondrow et al. (1982).

Discussion

The utilization of social assistance performance measurement methods employing DEA and SFA is relatively uncommon. The results of the frontier production function model, as presented in Table 4, indicate a negative correlation between the social assistance input variable and the poverty level output variable. The interpretation of these findings suggests that a rise in social assistance by 1 million IDR could potentially lead to a decrease in the poverty rate by 0.061%. Although the impact of social assistance on the poverty rate lacks statistical significance, this negative relationship aligns with previous studies by Arfandi & Sumiyarti (2022) and Le-rong & Xiao yun (2021). Other research findings have demonstrated that food assistance packages and direct cash assistance contribute to enhancing the survival of individuals facing poverty (Pramanik, 2020).

Table 5 Efficiency results derived from SFA models

Residences	Year	Technical Efficiency	Residences	Year	Technical Efficiency
West Halmahera	2015	0.765	Morotai Island	2015	0.538
	2016	0.718		2016	0.385
	2017	0.651		2017	0.454
	2018	0.698		2018	0.449
	2019	0.727		2019	0.459
	2020	0.735		2020	0.417
	2021	0.734		2021	0.449
South Halmahera	2015	0.786	Taliabu Islands	2015	0.387
	2016	0.679		2016	0.324
	2017	0.732		2017	0.395
	2018	0.769		2018	0.372
	2019	0.827		2019	0.386
	2020	0.835		2020	0.375
	2021	0.730		2021	0.412
Central Halmahera	2015	0.703	Ternate Island	2015	0.586
	2016	0.539		2016	0.477
	2017	0.384		2017	0.611
	2018	0.582		2018	0.600
	2019	0.605		2019	0.659
	2020	0.673		2020	0.704
	2021	0.618		2021	0.713
East Halmahera	2015	0.816	Tidore Island	2015	0.444
	2016	0.823		2016	0.419
	2017	0.849		2017	0.513
	2018	0.818		2018	0.509
	2019	0.878		2019	0.535
	2020	0.894		2020	0.567
	2021	0.900		2021	0.492
North Halmahera	2015	0.722	Sula Islands	2015	0.651
	2016	0.593		2016	0.656
	2017	0.662		2017	0.735
	2018	0.682		2018	0.717
	2019	0.741		2019	0.716
	2020	0.747		2020	0.705
	2021	0.835		2021	0.600

Addressing poverty through social assistance programs is a key agenda for the Indonesian government. Post-COVID-19 economic recovery efforts persist with the implementation of various social protection policies. These initiatives aim to sustain the consumption levels and purchasing power of the poor population through social assistance, subsidies, and price stability maintenance at the consumer level. However, the implementation of government social aid in Indonesia encounters challenges, notably the inaccuracies in targeting beneficiaries and the brief duration of the programs. The social protection program is considered to have no impact on reducing poverty levels (Nurias et al., 2023).

Technical barriers in effectively allocating social aid to the intended recipients render social assistance programs ineffective in assisting the poor and vulnerable. The findings from both DEA and SFA indicate that the average technical efficiency of social assistance programs across all districts and cities in North Maluku Province is below one, categorizing them as inefficient (refer to Table 6). These results underscore the need for targeted interventions to address the inefficiencies in the allocation and distribution of social aid, thereby enhancing the effectiveness of these programs in alleviating poverty and supporting vulnerable populations.

Table 6 Comparing Efficiency Estimates by DEA and SFA Models

Regions	Average (2015-2021)	
	SFA	**DEA-CCR**
East Halmahera	0.854	0.971
South Halmahera	0.765	0.710
West Halmahera	0.718	0.763
North Halmahera	0.712	0.526
Sula	0.683	0.611
Ternate	0.621	0.410
Central Halmahera	0.586	0.505
Tidore	0.497	0.402
Morotai	0.450	0.266
Taliabu	0.379	0.248

Several obstacles hinder the effectiveness of social assistance programs in the region. One significant challenge is the prevalence of non-credible and illegal social institutions that receive aid, as many of them lack legal status. For instance, in East Halmahera Regency, instances were found where individuals who had relocated to other villages still received assistance from their original villages. Moreover, there were cases of misappropriation of cash assistance by individuals purporting to manage social institutions. Consequently, recipients often perceive the assistance as insufficient to improve their economic well-being. Furthermore, conflicts arise when affluent individuals receive social assistance while those in greater need are left out.

The distribution of social assistance also faces issues, such as significant deductions made by village administrators to cover operational costs, resulting in recipients receiving amounts lower than what the government stipulates. Moreover, non-cash assistance, like rice, cooking oil, and sugar, is sometimes deemed ineffective due to its limited utility. Inaccuracies in targeting beneficiaries stem from discrepancies in poverty data between regional and central government agencies. Harmonizing poverty data collection methods and definitions is crucial to mitigate this issue. Additionally, the annual publication of poverty data is inadequate given the dynamic nature of poverty, especially in island-based areas (Djuanda, 2024).

Enhancing social assistance in island communities requires advanced social service activities and improvements in assistance programs, such as business group empowerment initiatives (Kerr, 2005). However, challenges persist in providing capital for small and medium enterprises due to constraints like a lack of skilled workforce, technological proficiency, market access, and low product quality. Islands, characterized by small size and markets, struggle to achieve economies of scale in production and service provision, exacerbating these challenges (Fernandes & Pinho, 2017).

Budget planning for social assistance in archipelagic districts faces significant constraints, primarily due to limited funding. For instance, in North Maluku Province, before the COVID-19 pandemic, the average social assistance budget was less than IDR 10 billion annually. However, during the COVID-19 period, there was a significant increase in the budget, averaging more than IDR 50 billion and even reaching IDR 300 billion. Despite this increase, the augmented budget for social assistance during COVID-19 was deemed inadequate to bolster the economic resilience of the poor in the archipelago. On average, the poverty rate in all districts and cities in North Maluku Islands Province surged by 0.5%. Efforts to provide production facilities for groups of farmers and fishermen often do not align with their needs and preferences. Consequently, endeavors to enhance the income and business development of poor island communities have been largely unsuccessful. These challenges underscore the complexities involved in effectively addressing poverty in archipelagic regions and highlight the necessity for tailored and sustainable strategies to uplift the economic well-being of these communities.

Conclusion

The article examines the performance and impact of social assistance on regional poverty rates. Both the DEA and Stochastic Frontier analyses indicate that social assistance programs across all research areas are inefficient in reducing poverty. Key obstacles identified include the limited budget allocation, inaccuracies in targeting assistance recipients, and insufficient distribution period, which contribute significantly to the inefficiency of these programs.

Ensuring the efficiency of social assistance distribution requires the integration of updated poverty data into a unified system. Accurate targeting and timely distribution are essential for enhancing the effectiveness of social assistance programs in poverty reduction. Additionally, increasing the assistance amount can be achieved by synergizing programs between government agencies, thereby maximizing the benefits for poor communities in villages.

A notable limitation of the study is the small number of variables utilized in the efficiency model. Future research should explore additional variables related to social assistance, which may have implications for effectively reducing the poverty rate in island areas. By addressing these limitations, future studies can provide a more comprehensive understanding of the factors influencing the effectiveness of social assistance programs in poverty alleviation.

Author Contributions

Conceptualisation, CA.IZ.FD and RBH.; Methodology, CA. ITAR; Investigation, MH.NM; Analysis, CA.FD.; Original draft preparation, CA.CJA; Review and editing, CA.RBH.

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Conflicts of Interest

The authors confirm no conflict of interest. The authors are responsible for the content and writing of this article.

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