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ARTICLE

Government Intervention Strategy in Poverty Reduction

Study on the District and City in Indonesia Across 2016–2023

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Abstract: Poverty remains a significant challenge in Indonesia, with a national rate of around 9.36% in 2023 and 16 provinces exceeding this poverty level. This study aims to analyze poverty patterns across districts and cities by using K-Means Clustering and examine the effectiveness of government interventions in poverty reduction through panel data regression with the Fixed Effect Model (FEM). Results indicate that higher-poverty areas benefit most from social assistance, village funds, credit schemes, and GRDP, while capital spending exacerbates poverty. On the other hand, lower-poverty areas achieve reductions through capital spending, village funds, and GRDP, with minimal impact from social assistance and credit schemes. Also, these results emphasize the need for targeted interventions, such as optimizing social assistance and credit access programs in higher-poverty areas and implementing growth-focused strategies, including physical infrastructure development, in lower-poverty regions.

Keywords: Poverty Reduction; K-Means Clustering; Local Government Expenditure; Government Credit Program.

1. Introduction

Poverty is an aspect that cannot be separated from the country's economic development. The inability of a community to meet decent living needs will affect the quality of welfare, including basic needs, education, and health. Additionally, the inability of the community to improve their standard of living will also have an impact on inhibiting national development in the long term (Fransiska R et al., 2022).

Poor people are defined as groups who cannot meet the standard of living set within a system (Lister, 2021). Jolliffe and Prydz (2016) explained that the world's poverty measurement—based on the World Bank —is determined by the international poverty line (IPL). Meanwhile, the measurement of poverty in Indonesia is measured through the poverty line, which the Central Statistics Agency periodically releases.

Adji et al. (2020) stated that the poverty line in Indonesia measures the expenditure or income required to meet basic food and non-food needs for a decent living. Thus, the poverty rate is calculated by comparing the number of people living below the poverty line with the total population in an area (Ferezagia, 2018).

In his research, Adji et al. (2020) state that poverty is divided into two general categories: absolute and relative poverty. The concept of absolute measurement is based on the inability of individuals to survive with expenses below the absolute poverty line. Relative poverty uses a poverty line that is relatively determined by the welfare level of the population in a particular area (Rachmawati, 2020; Rahman et al., 2019).

Eguruze et al. (2023) stated that the problem of poverty has a very high level of complexity. Poverty can be caused by unemployment, low wages, low levels of education, high and uncontrollable inflation, injustice distribution of opportunity among the income groups, discrimination, difficult geographical access, and so on.

Moreover, the root of poverty is also connected to the impact or effects of poverty. Islami and Anis (2019) argue that impoverishment is a symptom where a society is powerless to fulfill the quality of their education and health. As a result, the community's ability becomes limited. This condition impacts the process of improving the quality of education, health, and access to other opportunities to improve the standard of living, indirectly reducing the quality of human resources (Maulana et al., 2022) and minimizing the opportunity to escape from the chain of poverty.

Several studies have confirmed how difficult it is for poor people to improve their welfare. Children living in deprivation tend to have more limited prospects in the future. From a health perspective, children from disadvantaged backgrounds are more susceptible to disease and have a higher potential to experience mental health disorders (Sultanova, 2024). From the educational perspective, Jones et al. (2020) found that barriers to academic success significantly occur among disadvantaged communities.

Poverty in Indonesia as of March 2023 showed a fairly high level, reaching 25.9 million people or around 9.36% of the population (BPS, 2023). Based on BPS data in Figure 1, the average poverty rate of districts/cities in Indonesia from 2016 to 2023 has a downward trend, from 13.2% in 2016 to 11.5% in 2023. The highest poverty level also experienced an improvement in the same period, declining from 43.4% in 2016 to 37.7% in 2023. However, the lowest poverty percentage (P0) indicator increased by 0.6 percentage points in 8 years.

The issue of inequality also aggravates poverty-related problems in Indonesia. The distribution of poverty across provinces—and even between regions—is uneven.

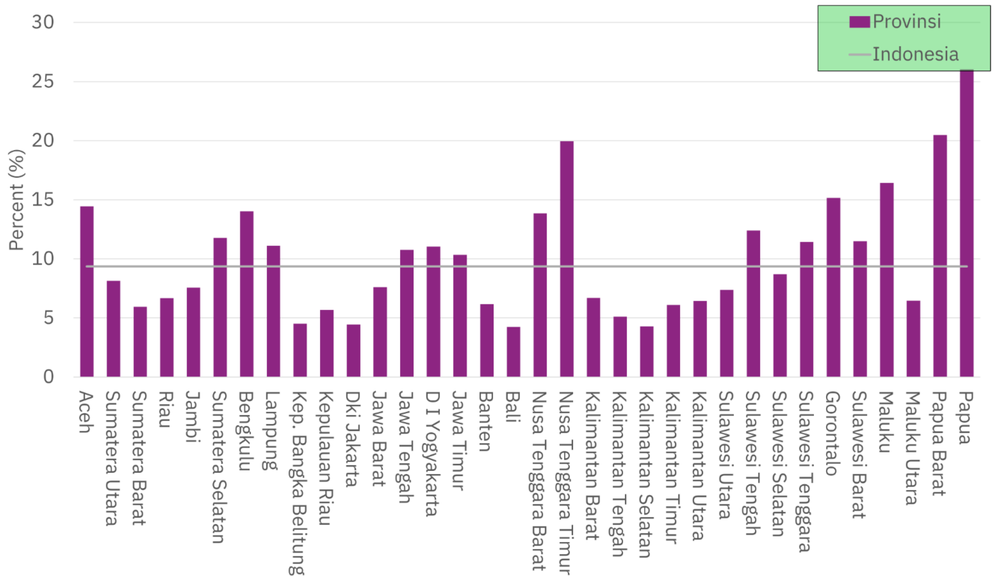

Figure 1. Poverty Level (P0) by Province in 2023

Source: BPS (processed)

Figure 2. Percentage of Poor People by Regency/City (p0)

Source: BPS (processed)

As shown in Figure 2, there is a significant disparity in poverty levels between regions with the highest and lowest poverty populations. On the other hand, Figure 1 explains how poverty records at the province level show that there are still 16 regions with poverty levels above the national level in 2023, most of which are in the Sulampua region (Sulawesi-Maluku-Papua).

As a regulator, the government plays a crucial role in addressing poverty in Indonesia. The government is expected to provide adequate public services by leveraging various fiscal tools, especially in improving community welfare (Sunardi et al., 2022). Through the application of good governance principles and strict budget accountability (Fatoni, 2020; Sunardi et al., 2022), the government can maximize the usage of expenditure instruments to build physical infrastructure to emerge the multiplier effect on the economy (Nugroho et al., 2022) and serves as a proxy for poverty reduction.

Government capital expenditure, in particular, has a significant multiplier effect on economic growth. Several studies have found that the provision of infrastructure facilities—such as roads, ports, airports, and electricity and water accessibility—accelerates economic growth and opens up other economic potential (Dudzevičiūtė et al., 2018; Rivenbark et al., 2018; Sunny & Olufemi, 2023). Improvement of physical infrastructure will encourage people and logistics mobility between regions. Quality capital expenditure can directly boost economic activity, reduce distribution costs for goods and services, increase labor mobility between regions, and open up opportunities for new industries.

Therefore, the government shall be encouraged to optimize the execution of its capital budget. Based on the Regulation of the Minister of Finance (PMK) Number 62 of 2023 on Budget Planning, Budget Implementation, and Financial Accounting and Reporting, capital expenditure refers to any budget expenditure aimed at acquiring or adding assets that provide benefits for more than one accounting period (12 months) and exceed the minimum asset capitalization threshold. In practice, capital expenditure covers government spending on developing connectivity infrastructure, developing natural resource networks, building construction, purchasing official vehicles, and acquiring other assets as permitted by the regulations. The capitalization threshold as outlined in Petunjuk Teknis Akuntansi 15 by Direktorat Akuntansi dan Pelaporan Keuangan (2023) includes:

a. Equal to or above Rp1,000,000 for equipment and machinery purchases, and maintenance of equipment and machinery fixed assets; and

b. Equal to or above Rp25,000,000 for the acquisition of buildings and structures and maintenance of building and structure fixed assets.

Poverty alleviation strategies are not only limited on infrastructure development or capital spending. Sigit and Kosasih (2020) proposed several strategies in optimizing village funds to reduce poverty in the regions, such as enhancing supervision, perfecting the formulation of village funds, and improving the allocation process for Village Fund Allocation (ADD).

Village funds are a financial transfer instrument to villages sourced from the National Budget (APBN) (Chasanah et al., 2017). Village funds are utilized as a village's source of income in executing the governmental duties, fostering village development, community empowerment, and financing the priority village programs (Raharjo, 2020) thus becoming vital to reducing inequality and poverty (Saragi et al., 2021). In addition, a portion of the village funds has been earmarked for the allocation of Direct Cash Assistance (BLT) to the poor.

The pattern of village fund management in 2024 has shifted with the division of village fund posts, whose usage is not determined, and village funds, whose usage is determined. According to PMK Number 146 of 2023, village funds whose usage is determined are intended for funding programs related to economic recovery, such as social protection and handling extreme poverty in the form of Village BLT, food and animal security programs, and/or stunting prevention programs. A mandatory budget in village funds is a strategic means to achieve national development targets.

Not only using the village funds, the central or regional government could also use social assistance spending instruments to provide a safety net for the underprivileged from social risks, especially for those facing extreme poverty. Social risk is a vulnerability arising as a result of economic crises, political crises, and natural disasters (Dharmakarja, 2017) To prevent this vulnerability, the government can administer social assistance spending in the form of money, goods, or services as stated in PMK Number 62 of 2023.

The provision of government social assistance has a special mission of reducing income inequality among income groups and poverty levels (Yasni & Yulianto, 2020). The effectiveness of such fiscal instruments is highly dependent on the accuracy of the recipients. Misallocations of social assistance will further increase the income gap among social groups.

In addressing the poverty problem effectively, empowerment in the economic activities of the poor people is necessary. In their paper, Purwadi et al. (2023) mention a practical example of a poverty alleviation strategy through increasing the business capacity. People's Business Credit (KUR) and Ultra Micro (UMi) are credit schemes provided by the government that offer financing solutions for strengthening Micro, Small, and Medium Enterprises (MSMEs). Strengthening MSMEs is an inclusive economic development strategy based on their economic and social potential for the poor, as stated by Malelak et al. (2020).

The scalability of MSME businesses has consequences for the growth of business funding needs. However, conventional credit often comes with relatively more difficult application requirements. Through the KUR and UMi schemes, the government is trying to provide alternative loans with subsidized interest rates, the amount of which is regulated in the Regulation of the Coordinating Minister for Economic Affairs Number 1 of 2023 on Amendments to the Regulation of the Coordinating Minister for Economic Affairs of the Republic of Indonesia Number 1 of 2022 concerning Guidelines for the Implementation of People's Business Credit, and PMK Number 193 of 2020 about Ultra Micro Financing.

Elliyana et al. (2020) found that KUR positively impacted the income of MSMEs in Sigeri District, Pangkep Regency. In another study, the positive effects of KUR were also reported in MSME business activities in the Wonosobo area (Marfuah & Hartiyah, 2019) and Tarus Village (Malelak et al., 2020).

With various types of spending and budget constraints, the government must be careful when allocating resources to address poverty. Some regions may have different poverty characteristics. Therefore, addressing poverty requires understanding these distinctions, as solutions for each type might differ (Matondang, 2017). It is necessary to adjust the strategy for the government interventions.

In this study, the author tries to dig deeper to answer the question, “Which government interventions have better impact on poverty reduction?”. Thus, regulators can adjust the policy strategies for each poverty group in Indonesia. A quantitative approach will accommodate data from districts and cities in Indonesia for around 8 years (2016-2023). The study will examine how government instruments—such as regional capital expenditure, regional social assistance expenditure, and village funds—play a role in alleviating poverty. In addition to expenditure instruments, the author accommodates government credit subsidy policies—Kredit Usaha Rakyat (KUR) and Ultra Mirko (UMi)—which MSMEs widely use in the regions. The Gross Regional Domestic Product (GRDP) variable will also be considered in the calculation process to see how economic growth can contribute to poverty improvement.

Ideally, the high normal GRDP and economic growth (Constant GRDP Growth) should improve community welfare. This is reinforced by Giovanni (2018), which shows an improvement in poverty levels on Java Island alongside economic growth. However, the findings and ideal theories are not always aligned with data from BPS, which records that several regions—such as Central Sulawesi, Central Java, and Papua—have relatively high poverty rates compared to their size and economic growth. In Bintang and Woyanti's research (2018), GRDP growth in Central Java has a positive effect or increases the poverty rate. These counter-theoretical cases like this need to be studied more deeply as input in formulating government policies so that economic growth that occurs in a region can provide inclusive benefits to all community groups.

In this study, data processing will be done by mapping regions in Indonesia based on poverty levels through clustering using the K-Means Method and continuing with the panel data regression method. The k-Means method is popular for clustering data (Sinaga & Yang, 2020). The advantage of K-means lies in the simplicity of its method, which is based on the centroid or midpoint of the cluster (Saputra et al., 2020). Furthermore, Saputra et al. (2020) explained that K-Means clustering begins by randomly placing centroids according to the k value (number of clusters) initiated by the user.

In determining the ideal number of clusters, the initiation of the k value or the number of clusters can be used as the basis for looping or repeating the program. Furthermore, the distance and silhouette value calculations are carried out for the number of related clusters for each repetition session. After the looping process is complete, the number of clusters can be determined by selecting the k value with the highest silhouette coefficient.

Distance calculation in the k-means method can utilize Euclidean Distance, Manhattan Distance, or the Minkowski Distance. The distance calculation in question accommodates between data points and the centroid or midpoint of the cluster. Furthermore, silhouette coefficient calculation is carried out to measure the similarity of data points with their clusters and other clusters (Sinaga & Yang, 2020). The silhouette score range extends from -1 to +1, with values approaching +1, indicating a better clustering.

As mentioned earlier, the combination of regional clustering and panel data regression is designed to assess the impact of government interventions on poverty across different poverty clusters. Clustering regions enables the government to gain deeper insights into the specific characteristics of poverty in each area. By applying panel data regression analysis, this study identifies which intervention instruments deliver the greatest impact on poverty reduction for each cluster. The study emphasizes that there is no one-size-fits-all solution to alleviating poverty. Fiscal instruments must be carefully weighed and adjusted based on the regional characteristics. While some regions may share similar poverty traits, effective poverty reduction strategies cannot be replicated without considering the distinct local context. Thus, this approach enables the government to utilize policy instruments that are most appropriate for each regional poverty cluster.

2. Methods

2.1. Data and Analysis Methods

The analysis method in this paper employs a quantitative method based on secondary data that can be accessed from official government applications/ websites. Researchers take poverty and GRDP data from the publication of the Central Statistics Agency (BPS). At the same time, regional capital and social assistance expenditures are obtained via the Directorate General of Fiscal Balance (DJPK) website, Ministry of Finance. The village fund is collected from an application provided by the Directorate of Budget Execution, Directorate General of Treasury, Ministry of Finance. Meanwhile, the author accesses data on KUR and UMi distribution through the SIKP application of the Ministry of Finance.

The independent variables in this study are capital expenditure, regional expenditure, village funds, KUR & UMi, and GRDP. Meanwhile, the impact of the independent variables is tested on the dependent variable, which is the number of poor people.

The dataset in this study consists of a combination based on entities (Districts/Cities in Indonesia) across a time span (2016-2023). Therefore, the panel data regression analysis method will be applied to accommodate coefficient estimation between individual entities and time using Fixed Effect Model, Random Effect Model, or Common Effect Model (Munandar, 2017). Before carrying out the regression analysis, the data in this study will be clustered using the K-Means method to determine the poverty clusters of the Regencies/Cities.

2.2. Research Flow

The analysis in this study begins by collecting secondary data from various relevant and credible sources. In the next step, the author cleans the data on poverty, capital expenditure, social assistance realization, village funds, KUR UMi distribution, and GRDP per Regency/City during 2016-2023. Data cleaning involves eliminating incomplete and irrelevant entries to ensure data compatibility in the clustering and regression process.

Before proceeding to the clustering stage, the data enters the descriptive analysis phase. Descriptive analysis is a step in describing data to make it easier to recognize and understand. In this paper, descriptive analysis is used to find the average, minimum value, maximum value, standard deviation, and other relevant information.

The K-Means clustering method is then applied to map districts/cities based on poverty levels. This algorithm is widely favored for its simplicity, scalability, and efficiency in handling large datasets, making it one of the most popular clustering techniques in data analysis (Ikotun et al., 2023). Furthermore, researchers have been running on improving the algorithm, such as (Ashabi et al., 2020) who proposed parallel processing techniques to boost performance and scalability.

The process begins by determining the number of clusters, typically k=2. Then, the algorithm iteratively performs the clustering process, which includes calculating evaluation metrics like silhouette scoring and/or distance calculations until it reaches the maximum looping point (max_k) set by the user. By identifying the optimal evaluation value—e.g., the highest silhouette coefficient—the algorithm determines the most effective division of data points into clusters. In this study, the final output identifies an optimal number of clusters that represent poverty levels, providing valuable insights into the distribution and characteristics of poverty across different regions in Indonesia.

These cluster results are used as a reference for multiple linear regression to map the impact of the independent variables according to poverty characteristics. In the regression process, the author also enacted the Langrage Multiplier, Chow, and Hausman Test to choose the best regression model among the Fixed, Random, or Common Effect Models. Furthermore, the validity of the regression results is tested through classical assumption tests, determinant tests, simultaneous tests, and partial tests before the final interpretation of the analysis results.

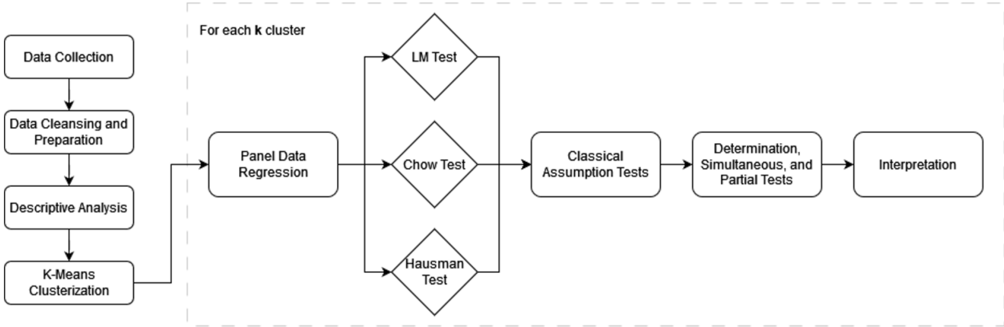

Figure 3. Research Flow of Government Intervention Strategy in Poverty Alleviation

Source: Authors

3. Results and Discussion

3.1. Descriptive Analysis

The author cleaned up incomplete data or missing values to hinder bias in the regression results. The data cleaning process left 3,864 rows, about 93.97% of the initial data. The attrition or data loss rate (6,03%) is justified by a study by Cheng and Trivedi (2015) and Gustavson et al. (2012) who conducted studies with a much higher data attrition rate. Furthermore, Gustavson et al. (2012) studied data loss rates between 30% and 70%, likely affecting the interpretation for generalization purposes. Some areas that were excluded from the process include Yalimo Regency, Tolikara Regency, Deiyai Regency, etc, due to the missing value of one or more variables.

As a result, the total number of data observations stands at 3,864 data points, with an average percentage of poor people (PO) of 11.4%. Furthermore, in the descriptive analysis, capital expenditure of 483 regencies/cities from 2016 to 2023 has an average of IDR298.5 billion, social assistance spending reaches IDR10.57 billion, village funds have an average of IDR125,49 billion, government credit distribution (KUR & UMi) is recorded at IDR397.3 billion, and the average GRDP is IDR18.84 trillion. Table 1 shows how high the standard deviation and the difference between the minimum and maximum values for each variable. For example, the standard deviation for capital expenditure reaches IDR228.44 billion with a difference between the minimum and maximum spending realization of IDR2.74 trillion.

Table 1. Descriptive Data Analysis on 483 Regions 2016-2023

	Poor People (Head Count)	P0 (%)	Capital Exp (Bil. IDR)	Social Ass. Exp. (Bil. IDR)	Village Funds (Bil. IDR)	KUR & UMi (Bil. IDR)	GRDP (Bil. IDR)
count (N)	3.864	3.864	3.864	3.864	3.864	3.864	3.864
mean	52.467	11,40	298,50	10,57	124,49	397,38	18.941,92
stdev	58.950	6,37	228,44	25,49	104,12	516,13	32.479,53
min	1.230	1,67	17,93	0,00	0,00	0,00	116,64
Q1	15.247	6,79	169,54	0,86	52,12	81,01	3.997,10
Q2	28.865	9,98	238,39	3,67	104,44	202,59	9.327,61
Q3	69.322	14,33	345,10	10,77	173,34	501,93	19.956,40
max	491.240	39,46	2.754,30	485,44	639,06	4.550,05	459.030,70

Source: BPS; DJPK; Directorate of Budget Execution, DJPb; and SIKP (processed)

From a time series perspective, the average poverty rate of districts/cities shows a general downward trend. However, in 2020 and 2021, the poverty rate in Indonesia increased from the previous year (Figure 4) due to the Covid-19 pandemic, which hampered all aspects of life.

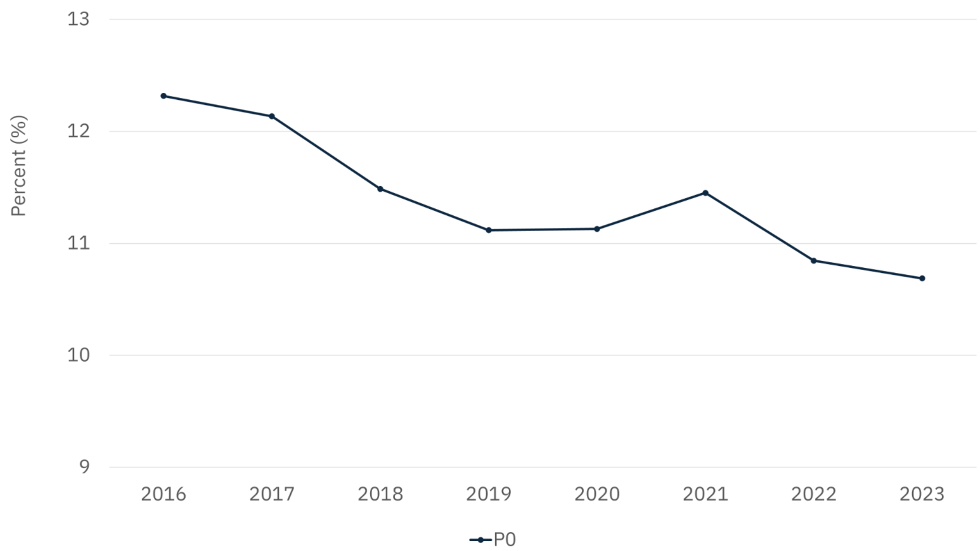

Figure 4. Average Poverty Rate (P0) by Regency/City Trendline

Source: *BPS (Processed)*

The realization of capital expenditure, social assistance, and village funds in Indonesia shows a fluctuating trend. The amount of government capital expenditure is based on the needs of the programs and activities to be implemented and the development targets. Social assistance expenditure is mostly budgeted based on the number of beneficiaries, with an average of IDR 9.3 billion in 2023, reflecting a yearly downfall from the covid pandemic era.

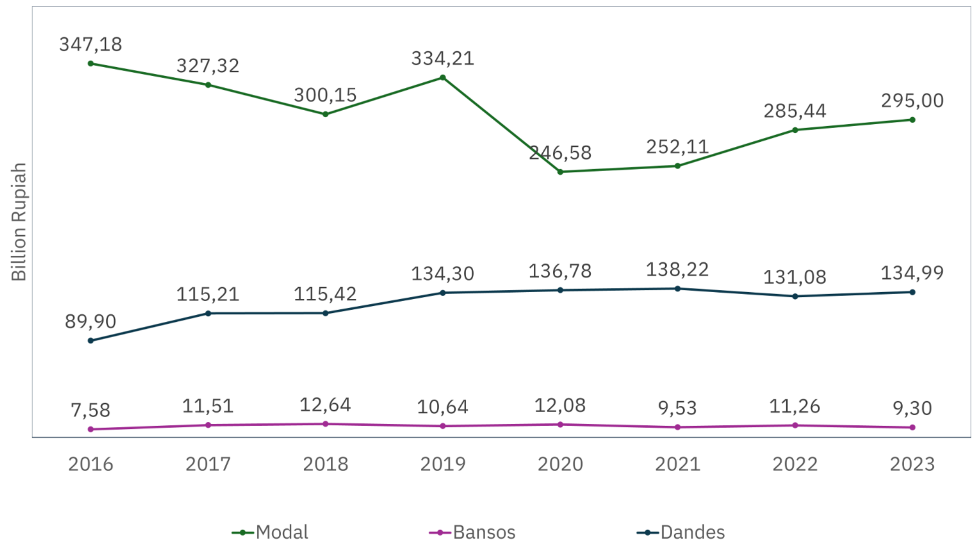

Figure 5. Averaging Capital Expenditure, Social Assistance, and Village Funds From 2016 to 2023

Source: *Directorate of Budget Execution, DJPb; and DJPK (Processed)*

3.2. Data Clustering

The clustering process is conducted with reference to poverty indicators represented by the percentage of poor people (P0), capital expenditure, social expenditure, village funds, government credit distribution (KUR & UMi), and GRDP. Adopting the research of Putrie and Sanjaya (2021), clustering of regional poverty levels is performed by accommodating the average of each variable/data within the research period.

In this study, the author initiates the clustering process by setting the initial kk value to 2 and the maximum number of clusters to 20. This assignment leads the algorithm to loop until the maximum cluster count, grouping data points iteratively based on the current cluster value (k). The silhouette score is calculated for each iteration to evaluate the clustering quality. This iterative process ensures that the optimal clustering configuration is identified.

The K-means clustering results in Table 2 demonstrate the silhouette coefficients for various clusters. The silhouette score evaluates the quality of clustering, where higher scores indicate better-defined and more cohesive clusters. For k=2k=2, the silhouette score is 0.8589, significantly higher than the scores for other values of kk. As kk increases, the silhouette score gradually decreases, with the lowest score of 0.5342 observed at k=20k=20. The substantial drop in the silhouette score starting from k=3k=3 suggests that increasing the number of clusters diminishes cluster cohesion and separation. Consequently, k=2k=2 is selected as the optimal number of clusters, offering a clear and meaningful division of poverty levels across regions.

Table 2. K-Means Clustering Looping Results

K-Cluster	Silhouette Score
2	0.8589
3	0.8214
4	0.6882
5	0.6544
...	
17	0.5560
18	0.5558
19	0.5558
20	0.5342

Source: *Data Processing with Jupyter Lab*

The K-Means method, processed through Jupyter Lab (Python), classified 463 districts/cities into the high-poverty cluster, while 20 districts/cities were labeled in the low-poverty cluster. The difference between the two clusters can be seen from the centroid information or the midpoint, which represents the average value in a certain cluster.

In more detail, Table 3 summarizes the centroids of each poverty cluster. Areas with high poverty have an average poverty rate of 11.58%, while low poverty clusters are estimated to have an average poverty rate of around 7.12%. The labeling of the poverty clusters is based on a relative comparison of the centroid conditions of each cluster.

Table 3. K-Means Cluster Centroid

Cluster	Region Count	P0 (%)	Capital Exp. (Bil. IDR)	Social Ass. Exp. (Bil. IDR)	Vil. Funds (Bil. IDR)	KUR & UMi (Bil. IDR)	GRDP (Bil. IDR)
High Poverty	463	11,58	273,86	9,99	123,38	366,58	13.807,30
Low Poverty	20	7,12	868,85	23,91	150,10	1.110,42	137.808,20

Source: *Data Processing with Jupyter Lab*

Another characteristic seen in Table 3 is the difference in the government instruments and economic indicators between clusters. The execution of capital expenditure, social assistance expenditure, village funds, government credit, and realization of GRDP in the low-poverty cluster has a higher nominal value than in the high-poverty cluster. This shows that increasing government intervention should be able to encourage a decrease in poverty levels.

In addition, the high provision of soft credit programs from the government in the KUR & UMi scheme has a role in encouraging the scalability of MSMEs and helping to build the economy from the lower-middle class. On the other hand, regions with high economic output indicate a trickling-down effect in improving people's welfare.

3.3. Panel Data Regression

Panel data regression in this study will have two forms of models: low poverty and high poverty. The dataset in each model refers to the regions in each cluster with a time series from 2016-2023. Determination of the panel data model and tests will be carried out independently—without any connection between one model and another. The equation model in panel data regression for low poverty and high poverty is formulated as follows:

$$ln(jiwa\_miskin_{ij}) = \beta_0 + \beta_1 ln(modal_{ij}) + \beta_2 ln(bansos_{ij}) + \beta_3 ln(dandes_{ij}) + \beta_4 ln(kreditpem_{ij}) + \beta_5 ln(pdrb_{ij})$$

With variable descriptions including:
jiwa_miskin is the number of poor people.
modal represents local government capital expenditure in IDR.
bansos is the realization of social assistance spending issued by the regional government in IDR.
dandes is a variable for the amount of village fund distributed in IDR.
kreditpem represents the amount of KUR and UMi credit shared out in IDR.
pdrb is a constant Gross Regional Domestic Product (GRDP) variable for each district/city at current period of time in IDR.
i, j are denotations of entity (district/city) and time (year).
β_0 connotes a constant in linear regression.
$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are variable coefficient that also shows the magnitude of the impact of the independent variable on the dependent variable.
ln() is a natural log function used to transform the variable values in this study.

Table 4. Model Selection Test Results

Model 1 – High Poverty Cluster		
Test Type	**Probability**	**Selected Models**
Lagrange Multiplier	0.0000	REM
Chow	0.0000	FEM
Hausman	0.0000	FEM
Model 2 – Low Poverty Cluster		
Test Type	**Probability**	**Selected Models**
Lagrange Multiplier	0.0000	REM
Chow	0.0000	FEM
Hausman	0.0000	FEM

Source: *Data processing with Eviews*

By processing the data with Eviews 13, LM, Chow, and Hausman, tests were performed on both regression models/clusters. As a result, the selected model for panel data regression on the high-poverty cluster is the Fixed Effect Model (FEM). The decision-making is based on the Lagrange Multiplier (LM) test, which shows a probability below the significance level (<0.05), thus eliminating the CEM model. The Chow test shows a chi-square probability <0.05 and indicates the selection of the FEM model. Furthermore, the selection between FEM and REM is determined by the Hausman test, with the results of selecting FEM as the best model because the probability value indicates rejection of REM.

The second equation model for the low poverty cluster also shows that FEM is the best model. This is supported by calculations in Eviews 13 (Table 4), which show that the results of the LM test and the Chow test reject the possibility of CEM as the selected model, and the Hausman test records a probability below the significance level.

According to Septianingsih (2022), classical assumption testing for FEM will be focused on multicollinearity and heteroscedasticity detection. Multicollinearity testing uses the Variance Inflation Factors (VIF) indicator or correlation coefficient. For heteroscedasticity detection, Uyanto (2022), in his study, he mentioned several methods, such as the Breusch–Pagan test, Glesjer test, Goldfeld–Quandt test, Harvey–Godfrey test, Harrison–McCabe test, Park test, White test, or Monte Carlo method.

Table 5. Multicollinearity Detection Results

Model 1 – High Poverty Cluster		
Variables	**VIF**	**Information**
modal	1.331768	Pass [VIF<10]
bansos	1.005525	Pass [VIF<10]
dandes	1.020959	Pass [VIF<10]
kreditpem	1.377698	Pass [VIF<10]
pdrb	1,774538	Pass [VIF<10]
Model 2 – Low Poverty Cluster		
Variables	**VIF**	**Information**
modal	1.240544	Pass [VIF<10]
bansos	1.116426	Pass [VIF<10]
dandes	1,186524	Pass [VIF<10]
kreditpem	1.385616	Pass [VIF<10]
pdrb	1.616401	Pass [VIF<10]

Source: *Data processing with Jupyter Lab*

The independent variables in model 1 and model 2 indicate that the variables are free from multicollinearity symptoms. This can be seen from the VIF value, which is below 10, as presented in Table 5. The general multicollinearity threshold (rule of thumb) is above 10; even a VIF value of more than 5 can also contribute significantly to multicollinearity (Marcoulides & Raykov, 2018).

Table 6. Results of the Goldfeld-Quandt Test for Heteroscedasticity

Model 1 – High Poverty Cluster		
Goldfeld-Quandt Test	**Value**	**Information**
GQ Statistics	0.820144	Passed
GQ Probability	0.999990	[Prob > 0.05]
Model 2 – Low Poverty Cluster		
Goldfeld-Quandt Test	**Value**	**Information**
GQ Statistics	0.911634	Passed
GQ Probability	0.654138	[Prob > 0.05]

Source: *Data processing with Jupyter Lab*

The decision-making indicator for heteroscedasticity detection, as stated by Puspitasari et al. (2023) is based on the probability above the significance level (>0.05). Thus, the results of the Goldfeld-Quandt Test for equation models 1 and 2 can be stated that both models are free from heteroscedasticity symptoms.

The results of panel data regression with FEM show that the determinant coefficient (R-square) of model 1 regression is at 99.67%. The R-square level indicates that the independent variables can explain 99.67% of the changes in the dependent variable, while other factors outside the regression equation explain the rest or 0.37%.

Table 7. Fixed Effect Model Regression Results

Model 1 – High Poverty Cluster				
Variables	**Coefficient**	**Std. Err**	**t-Stat**	**Prob.**
C	10,9981	0.1682	65,388	0.0000
modal	0.0139	0.0035	3,9730	0.0001
bansos	-0.0005	0.0002	-2,0327	0.0422
dandes	-0.0124	0.0026	-4,7188	0.0000
kreditpem	-0.0012	0.0006	-2,1814	0.0292
pdrb	-0.0256	0.0039	-6,6129	0.0000
Effects Specification Cross-section fixed (dummy variables)				
R-square	: 0.9967	F-statistic	: 2077.29	
Adj. R-squared	: 0.9962	Prob(F-stat)	: 0.0000	
SE of regression	: 0.0624	Sum squared res.	: 12,6097	
Log likelihood	: 5268.62	AIC	: -2.5921	
Model 2 – Low Poverty Cluster				
Variables	**Coefficient**	**Std. Err**	**t-Stat**	**Prob.**
C	15,3303	2,0018	7,6581	0.0000
modal	-0.0132	0.0231	-0.5710	0.5689
bansos	0.0010	0.0015	0.6783	0.4988
dandes	-0.1398	0.0628	-2,2239	0.0278
kreditpem	0.0664	0.0166	3,9927	0.0001
pdrb	-0.0948	0.0558	-1.6993	0.0916
Effects Specification Cross-section fixed (dummy variables)				
R-square	: 0.9871	F-statistic	: 431,5367	
Adj. R-squared	: 0.9848	Prob(F-stat)	: 0.0000	
SE of regression	: 0.0861	Sum squared res.	: 1.0020	
Log likelihood	: 178,828	AIC	: -1.9228	

Source: *Data processing with Eviews*

On the other hand, the independent variables in the low poverty cluster equation can explain about 98.71% of the poor population variable. Thus, 1.29% of the change in the dependent variable is explained by factors or variables other than capital expenditure, social assistance expenditure, village funds, government credit, and GRDP.

Furthermore, the significance of the impact of independent variables is detected by the probability of an F-statistic. Each equation model shows a probability below the level of significance [Prob(F-stat.) < 0.05]. Table 7 suggests that the variables of mode of expenditure, social assistance expenditure, village funds, government credit (KUR & UMi), and GRDP together have a significant impact in determining changes in poverty in Indonesia.

In addition, the author tries to conduct a t-test or partial test to see the significance of each independent variable to the dependent variable. The measurement of partial significance uses a t-statistical probability reference below 0.05 (<0.05) for each independent variable in each poverty cluster.

The partial test results in the high poverty cluster show that each independent variable in the model 1 equation partially impacts poverty in Indonesia. The results of the Prob(t-stat.) calculation in Table 7 record a probability of 0.0001 (modal), 0.0422 (bansos), 0.0000 (dandes), 0.0292 (kreditpem), and 0.0000 (pdrb).

For equation model 2, 2 out of 5 independent variables have a partially significant impact. The variables are village funds (prob: 0.0278) and government credit (prob:

0.0001). In other words, the two variables can be stand-alone instruments to affect poverty problems in districts/cities with low poverty rates in the 2016-2023. Meanwhile, the other three variables need to be encapsulated together to encourage the significance of their effects on poverty.

The weight of the impact of the independent variables on the dependent variables for the high and low poverty cluster equations can be seen in the coefficients listed in Table 7. To facilitate interpretation, the constant values and variable coefficients are written into the equation model as follows:

$$ln(jiwa\_miskin_{ij}) = 10.998 + 0.0139 \times ln(modal_{ij}) - 0.0005 \times ln(bansos_{ij}) - 0.0124 \times ln(dandes_{ij}) - 0.0012 \times ln(kreditpem_{ij}) - 0.0256 \times ln(pdrb_{ij}) \quad [1]$$

$$ln(jiwa\_miskin_{ij}) = 15.330 + 0.0132 \times ln(modal_{ij}) + 0.0010 \times ln(bansos_{ij}) - 0.1398 \times ln(dandes_{ij}) - 0.0664 \times ln(kreditpem_{ij}) - 0.0948 \times ln(pdrb_{ij}) \quad [2]$$

3.4. Finding

Based on K-Means Clustering, poverty condition divides regions in Indonesia into 2, namely high poverty clusters and low poverty clusters. Clustering shows a significant difference in the percentage of poor people (P0) toward supporting factors such as government spending and economic conditions. Regions with low poverty have relatively higher resources (capital expenditure, social assistance, village funds, KUR & UMi distribution, and GRDP) than regions in the high poverty cluster.

In this case, including government intervention, resources are represented as organs in orchestrating poverty alleviation policies. Capital expenditure in regions in the low-poverty cluster reached an average of IDR868.85 billion during 2016-2023. Support for the MSME sector through the KUR & UMi scheme reached an average of up to IDR1.12 trillion for regions with low-poverty clusters, while the average government credit distribution for the high-poverty sector only reached IDR366.58 billion. Social assistance instruments were also recorded as higher on average for low-poverty clusters than high-poverty ones. The average calculation is used to explain how much value is obtained for each region and to avoid bias in summing numbers.

Put simply, high-poverty regions are characterized by limited access to critical resources and underdeveloped economic infrastructure, leading to weaker economic activity and fiscal capacity. Additionally, resource utilization in these areas is less effective, particularly in implementing programs such as village funds and KUR & UMi, which further hinder poverty alleviation efforts. In contrast, low-poverty regions benefit from better access to resources, stronger economic infrastructure, and more effective implementation of government interventions. These areas leverage fiscal and economic programs to create sustainable growth, lower poverty rates, and enhance resilience against economic challenges. Clustering or mapping is done to examine the impact of government intervention on poverty in Indonesia. The impact of government instruments can be different in each poverty cluster in Indonesia. Furthermore, the calculation of impact or weight is done by panel data regression with FEM as the selected model.

The coefficient of the independent variable represents the impact of factors on poverty reduction. In the 2016-2023 period, the regression results found that:

High poverty cluster – model 1:

a. The constant of the defined equation is 10.998, so it can be interpreted that naturally, there is poverty of 10.998 points or—if re-transformed with an exponential function—around 59,755 people.
b. Capital expenditure execution in high-poverty areas has a significant positive effect. Each point growth in capital expenditure realization will have an impact on increasing the poverty population by 0.0139 points. This may result from funds allocated to less impactful projects, such as prestige monuments, instead of essential infrastructure like roads, schools, or health facilities that directly boost economic activity. Poor budgeting priorities in economically disadvantaged regions can thus fail to reduce poverty effectively, sometimes even exacerbating it by diverting resources from critical needs. As an example, Jawa Timur Province (which regions is mainly clustered into high-poverty cluster) has struggled to effectively utilize capital expenditure to achieve quality economic growth that reduces poverty (Delen et al., 2019).
c. An increase in the realization of social assistance spending will significantly reduce poverty by 0.0005 points. This effect underscores the role of social assistance as a crucial intervention in mitigating poverty by directly addressing basic needs and providing temporary relief to the unfavored people, thus preventing any emerging social risk (Ihwandi & Khoirunurrofik, 2023).
d. The village fund instrument has a significant impact on reducing the number of poor people in the first cluster with an elasticity of -0.0124 points for every 1 point of village fund realization. This highlights the effectiveness of village funds in poverty alleviation by fostering grassroots-level, supporting community-based programs, improving rural infrastructure, and empowering local economies. To ensure the sustainability of this effectiveness, enhancing the capacity of village-level management is essential, as stated by Masbiran et al. (2021).
e. MSME support from KUR & UMi significantly reduces poverty by around 0.0012 points for every additional 1 point of outstanding. KUR & UMi have clearly promoted entrepreneurship and provided financial access to under-developed communities. By enabling small businesses to grow and create jobs, these instruments help uplift vulnerable populations, fostering economic empowerment and reducing poverty levels.
f. GRDP significantly helps to overcome poverty in areas with high poverty by -0.0256 points for each point. Economic growth can create employment opportunities, increase household incomes, and strengthen local markets, collectively reducing poverty. However, as noted in cases such as Arkum and Amar (2022), economic growth might exacerbate income inequality within a population.

Low poverty cluster – model 2:

a. In the absence of capital expenditure, social assistance, village funds, government credit, and GDP variables, poverty will constantly be at the level of 15,330 points for the low-poverty cluster.
b. Every one-point increase in the realization of capital expenditure in subnational areas with low poverty can help reduce poverty by 0.0132 points (simultaneously significant). This likely reflects better prioritization of economic development initiatives, strengthening the local economy and producing inclusive growth. By directing capital spending toward infrastructure and services that benefit a wide

range of residents, these regions can maintain steady economic activity thereby reducing poverty.

c. For every 1 point of social assistance spending realization, poverty will increase by 0.0010 points in the regions within the low poverty cluster. In these areas, social assistance may be poorly targeted or inefficient, offering limited benefits. In regions with lower poverty, such spending may not address the root causes of poverty and could even create dependency.

d. The distribution of village funds has a significant effect, partially and simultaneously, on reducing the poor population by around -0.1398 for every 1 point of growth in realization. Numerical-wise, this suggests that regions with lower poverty levels are more effective in managing village funds. It reflects the ability of local governments and communities to utilize these resources, ensuring a stronger impact on poverty alleviation by improving infrastructure and local economic.

e. The distribution of government credit has not impacted improving poverty alleviation. The variable coefficient shows a positive impact of 0.0664 points for every additional 1 point of distribution. This suggests challenges in effectively targeting credit programs, where demand may exceed supply in low-poverty regions due to a higher poor population than poor people count in high-poverty regions.

f. As the previous cluster, GRDP hurts poverty, amounting to -0.0948 points. This shows the consistency of the effect of economic growth on the issue of poverty.

Interpretation of the analysis results above provides an understanding of each independent variable's contribution to Indonesia's poverty rate. In the high-poverty cluster, social assistance, village funds, and MSME support through KUR & UMi significantly encourage improvements in poverty conditions in the region or successfully reduce the number of poor people. In addition, GRDP significantly impacts poverty reduction, indicating that economic growth has become a very important aspect of the poverty reduction strategy. In contrast, social assistance spending and KUR & UMi support were found to positively contribute to poverty—or simply, increasing poverty for each growth in the variable's value—in the low poverty cluster. Variables that show positive support (increase) poverty in several fiscal instruments indicate challenges in implementing the budget in a targeted manner.

Based on this description, the government can utilize insights from this analysis to adjust fiscal strategies and budget allocations. Strategic steps such as increasing the effectiveness of capital expenditures and optimizing the distribution of village funds can be more focused on areas with high poverty. Additionally, there needs to be an improvement in the distribution of government credit so that it has an impact on poverty reduction. With more targeted fiscal policy management and strategies that are adjusted based on economic conditions in each cluster, the government can encourage a more even convergence of poverty reduction throughout Indonesia.

4. Conclusion

Poverty conditions in Indonesia vary across regions. Some regions have relatively higher poverty rates than others, such as Central Java, which has a poverty rate of 10.77%, compared to West Java, which has a poverty rate of only around 7.62%. Additionally, the condition is exacerbated by the disparity in the declining rate of poverty among regions.

Using the K-Means Clustering method, the paper maps regions (regencies/cities) in Indonesia based on their poverty levels. The K-Means method found that regions in Indonesia are divided into 2 (two) poverty groups, namely high-poverty and low-poverty regions. The two clusters have quite significant differences. Regions in the low-poverty cluster have higher realization or absorption of capital expenditure, social spending, village funds, KUR & UMi distribution, and economic output (GRDP) than regions in the high-poverty cluster. In short, an overview of the conditions of each poverty cluster is:

a. The Low Poverty Cluster has an average poverty rate of around 11.58% with an average capital expenditure of around IDR 273.86 billion, social assistance expenditure of around IDR 9.99 billion, village fund absorption of IDR 123.38 billion, KUR & UMi distribution of IDR 366.58 billion, and an average economic output of IDR 13,807.30 billion.
b. The average poverty rate in the High Poverty Cluster was recorded at 7.12% with an average capital expenditure of IDR 868.85 billion, administered social assistance expenditure of IDR 23.91 billion, distributed village funds with a nominal value of IDR 150.10 billion, outstanding KUR & UMi of around IDR 1,110.42 billion, and an average GRDP of around IDR 137,808.20 billion.

Furthermore, the determinants of poverty reduction in all districts and cities in Indonesia from 2016 to 2023 are measured using the Fixed Effect Model (FEM) panel data regression method. Based on the regression results, the components of APBD capital expenditure, local government social assistance expenditure, village funds, government credit distribution (KUR & UMi), and the economy have varying impacts on each poverty cluster, such as:

a. Capital expenditure of APBD has an influence of 0.0139 points on the increase in poverty for each point of increase in the high-poverty area cluster. However, the influence of capital expenditure in low-poverty areas shows a coefficient of -0.0132 points.
b. In contrast, the coefficient of local government social assistance spending shows a negative impact of -0.0005 in the high-poverty cluster and increases poverty by 0.0010 in areas with low poverty.
c. Realizing village funds has a significant negative impact on reducing poverty levels in Indonesia, both in areas with high and low poverty clusters.
d. The impact of the government credit program in the form of KUR & UMi is quite diverse. In areas with high poverty, the distribution of KUR & UMi can encourage poverty improvement of around 0.0012 points. While in areas with low poverty, the effect of KUR & UMi distribution does not encourage poverty improvement.
e. The effect of economic growth on poverty is found to be consistent in both poverty clusters. Each point of GRDP growth will reduce poverty by 0.0256 points in high-poverty areas and by 0.0948 points in low-poverty areas.

Based on the results of the analysis, the government can encourage the optimization of state and regional instruments. The government's strategic steps to reduce poverty levels can be adjusted, such as:

a. Improve targeting mechanisms in low-poverty regions to ensure social assistance reaches vulnerable populations, avoiding inefficiencies and dependency. This can be done by refining the data of potential beneficiaries. Sub-region level data collection and validation are essential for this purpose.

b. Encourage the implementation of capital expenditures that impact marginalized communities in underdeveloped areas. Refocusing expenditure to budget projects that directly impact economic activity, such as infrastructure that improves connectivity to education, health, and trade.
c. Strengthen village funds management by enhancing capacity-building initiatives for village-level administrators to ensure efficient use of funds and empower communities through community-based programs.
d. Increase outreach and technical guidance for KUR & UMi schemes, particularly for MSMEs in agriculture and trade, to foster local economic growth and job creation.
e. Develop strategic fiscal and non-fiscal policies, such as partnerships with private sectors to create trade centers and other inclusive economic hubs that benefit marginalized groups.
f. Continue government programs on economic growth strategies that emphasize inclusivity, reducing disparities while maintaining economic expansion that benefits all dimensions and citizen groups.

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