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The Effectiveness of Targeting Food Assistance Program in Indonesia

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Abstract

In 2020, the food assistance program in Indonesia changed the method of distributing aid. The food assistance in the form of rice is now delivered electronically, using an electronic voucher that can be exchanged for food in in partner stalls. Transfer payment change was made to reduce the occurrence of targeting inaccuracies during aid distribution. This study aims to determine the success of the Sembako Program, which can be seen from the accuracy or inaccuracy of targets. The target accuracy rate in the Sembako Program is only 47.46 percent. Meanwhile, the exclusion error rate is 71.04 percent and the inclusion rate is 52.54 percent, higher than the target accuracy rates. In this research, exclusion error occurred in poor households with a younger head of household, no legal identity, no disabled household members, and having assets. Meanwhile, the inclusion error occurred in the opposite condition.

Keywords: food assistance program, transfer payments, exclusion error, inclusion error

1. Introduction

Today, poverty is still a common problem for the whole world, from middle-income to high-income countries. For low-income countries, the case is even worse. According to the World Bank, poverty in high-income countries did not reach 1 percent, but in low-income countries such as Sub-Saharan Africa, poverty reached 42.3 percent (Atamanov et al., 2020). As a middle-income country, poverty still exists in Indonesia, by 9.78 percent in March 2020 (Statistics Indonesia, 2020a).

One of the efforts to tackle poverty is addressing the root of the problem (Barrientos, 2010). Many countries globally, including Indonesia, have started implementing social protection programs for poor people and families. For instance, Hidrobo et al. (2018) reported 46 social protection programs, spread in 25 countries in Latin America, East and South Asia, and Sub-Saharan Africa. They claimed that social protection for low-income families could improve food security, increase the quantity and quality of food consumed, and increase assets. Further, Mykerezi and Mills (2010) researched the Food Stamp Program in the United States and found that the program can improve the food security of low-income families. Food assistance program in the form of food stamps is not only available in developed countries; some developing countries have also implemented them.

Food stamp programs are done as an important means of providing a safety net to the poor. Food stamps are given to households with incomes less than a certain value adjusted for the size of their household. Such food stamps can be used to purchase certain foods in authorized stores at non-subsidized prices. In Sri Lanka and Jamaica, income is self-reported by households. If there is no household income report, targeting can be done by proxy means test of some household member conditions such as illness, disability, malnutrition, unemployment, and old age. One of the main problems every country faces during the implementation of food stamp programs is identifying vulnerable households for food stamp targeting (Suryanarayana, 1995).

The implementation of food assistance programs in Senegal and Bangladesh, makes the recipient households have higher food security with more diversity of food compared to households that do not receive it (Hoddinott et al., 2020; Savy et al., 2020). This assistance provides benefits especially to very poor households (Savy et al., 2020). Food stamps implemented in Sri Lanka function effectively as income transfer. Housewives can be freer to determine the food they buy so that spending on food increases with food stamps (Suryanarayana, 1995).

Similarly, the Indonesian government pays special attention to the food assistance program. The government continues to improve the program from year to year despite still dealing with various challenges, including the design, target, administration, and implementation (McCarthy & Sumarto, 2018).

For over a dozen years after its implementation, Indonesia's food assistance program is still struggling to determine the precision of the target beneficiaries (Hastuti et al., 2008; Satriawan & Shrestha, 2018). Poor families who should be eligible for aid do not receive food assistance (exclusion error), while the non-poor families do receive the assistance (inclusion error) (Kusumawati & Kudo, 2019; Sutanto et al., 2020). Thus, to improve the accuracy of the targeted poor households, the government improves the database of beneficiaries by combining PMT (Proxy Means Test) and a community-based method (McCarthy & Sumarto, 2018).

The policy model must be followed by an appropriate distribution method to have a meaningful impact (World Bank Group, 2020). The direct distribution of rice (better known as Raskin and Rastra programs) raises various problems. Rice that should be aimed at poor households was instead distributed equally to all households (Sulaksono & Mawardi, 2012). In addition, missing food aid cases were found (Olken, 2006). This condition causes losses to the government because the allocated funds do not meet the target. Programs that are more targeted will provide better benefits for low-income families (Pangaribowo, 2012). The occurrence of exclusion errors leads poor households entitled to assistance to lose resources to meet their daily needs or get out of poverty. On the other hand, inclusion errors cause an increase in the cost of poverty reduction programs due to extra expenditure for households who are not entitled (Devereux et al., 2017).

To that end, the Indonesian government improves the distribution mechanism by switching to non-cash assistance in the form of electronic vouchers worth Rp. 110,000/family/month (USD 7.73/family/month). These vouchers can be exchanged for rice and eggs at partner stalls that distribute the food aid (called e-warong). This program is named Non-Cash Food Assistance (BPNT). The program was implemented gradually in big cities starting in 2017. By the end of 2019, it has been implemented in all parts of Indonesia. The program is expected to be more targeted so that the assistance can be received at the right amount and time (Coordinating Ministry on Human Development and Culture, 2017).

According to Ahmed et al. (2009), in their study on the food aid program in Bangladesh, the amount of assistance is important for poor families to meet their daily needs. In addition, along with inflation, the amount of food stamps also needs to be adjusted so that the goal to protect the poor is not eroded by inflation (Suryanarayana, 1995). In 2020, the Indonesian government increased the value of food assistance from Rp 110,000/family/month (USD 7.73/family/month) to Rp 150,000/family/month (USD 10.54/family/month). Average monthly per capita expenditure in 2020 in Indonesia amounted to Rp 1,225,685 (USD 85.98) while the March 2020 poverty line amounted to Rp 454,652 (USD 31.89) (Statistics Indonesia, 2020b). An increase in the amount of food aid will help poor households meet their needs by about 8 percent, assuming the average household member of 4 people.

Besides, the food scope was expanded to those containing carbohydrates, protein, vitamins, and minerals, following the needs of the beneficiary. Thus, this amount is hoped to meet the nutritional needs of beneficiary families, especially those who have children, to avoid stunting. For that reason, the program was called Sembako Program (Coordinating Ministry on Human Development and Culture, 2019).

Changes in the delivery mechanism cause an increase in the food assistance budget, as much as 35.1 percent or 28.1 trillion rupiahs (1.97 billion dollars) (Directorate of State Budget Preparation & Directorate General of Budget, 2020). However, the poverty rate is targeted to decline to 8.5 percent, which over the past two years has not been reached.

A program's success or failure in achieving the expected goals is not only determined by the program's appropriateness but also its effectiveness. One of the examples is the accuracy of the target implementation (Banerjee et al., 2021; Coady et al., 2004; Sumarto & Suryahadi, 2001). Changing the distribution method of food assistance, from cash to non-cash in the form of food vouchers, aims to reduce the inaccuracy during rice distribution in the Raskin and Rastra programs. By using vouchers, the accuracy is expected to rise because the government has full control. Therefore, the targeted beneficiaries will receive full benefits, and the assistance is not diverted to households that do not meet the requirements (Banerjee et al., 2021).

Several studies have been conducted in the past to investigate the implementation of food assistance. They concluded that there were still inaccuracies in targeting the beneficiaries, both inclusion errors and exclusion errors (Hastuti et al., 2008; Kusumawati & Kudo, 2019; Satriawan & Shrestha, 2018; Sutanto et al., 2020). This inaccuracy is not only caused by targeting errors but also errors during the implementation or distribution of the assistance programs (Devereux et al., 2017; Kusumawati & Kudo, 2019).

Scholars argue that targeting errors are caused by the mistakes in determining beneficiaries and implementation that are not following the established guidelines (Coady et al., 2004; Devereux et al., 2017). Harbitz and Tamargo (2009) revealed that the lack of legal identity documents led to exclusion errors in men and women. Poor people who do not have legal identity documents will find it difficult to obtain their rights as beneficiaries.

Besides the condition of the population or household directly, targeting performance can be stemmed from the condition of the area where the family lives. Inequality between regions in Indonesia, both socio-economic conditions and the ability of local governments, is an obstacle in poverty alleviation (World Bank, 2006). Regions with low income and income inequality have a lower chance to succeed in implementing poverty reduction programs (Coady et al., 2004; Devereux et al., 2017).

This research was conducted to provide information about the new food assistance program implemented in all provinces in Indonesia since 2020 with non-cash distribution methods. Research related to previous food assistance programs still uses cash distribution methods. The implementation of non-cash distribution methods previously has not reached all provinces in Indonesia so it cannot be compared between provinces. Using the latest datasets and multilevel binary logistic regression that has never been used before for similar research, this research is keen on investigating the success of the Sembako Program in Indonesia, especially concerning its targeting accuracy for each province. In addition, it aims to examine the types of conditions that make the target inaccurate, both exclusion and inclusion errors.

2. Sembako Program

The food assistance program in Indonesia has been around since 1998, named OPK (Special Market Operations). The program has seen several name changes (Raskin, Rastra, BPNT, and finally Sembako) as it continues to undergo improvements to increase its effectiveness in reducing poverty. Improvements are made to both the beneficiary database and the method of implementing the distribution of assistance. The Sembako Program is a food assistance program for poor families that was implemented in 2020.

The target of food assistance program recipients is 25 percent or as many as 15.6 million poor families. The Indonesian government improves the database of beneficiaries by combining PMT (Proxy Means Test) and a community-based method. The community-based method is carried out by involving local governments and communities through the FKP (Public Consultation Forum) to confirm the existence of poor and vulnerable households, reach out to other poor households that have not been registered, and mark inclusion errors. Household data collection is done to collect information about the condition of the house, socio-economic status of household members, and asset ownership conducted in 2015 called PBDT (Integrated Database Collection). From the results of the data collection a household ranking is constructed with PMT, which is a method of estimation by making a prediction model using regression techniques. The government used SUSENAS (National Socio-Economic Survey) data from 2011 to 2014 to measure how much influence each socioeconomic parameter had on the level of well-being/poverty seen from household spending. From the coefficient obtained, a prediction of household per capita expenditure is made using PBDT 2015 data (National Team to Accelerate Poverty Reduction, 2015). The results are named UDB (Unified Database) which is used by the Indonesian government to distribute various social assistance programs.

Improvements made to the Sembako Program from the previous food assistance program are the distribution of assistance carried out using e-voucher or non-cash which is expected to reduce the occurrence of exclusion errors and inclusion errors. In addition, increasing the value of assistance from Rp 110,000/family/month (USD 7.73/family/month) to Rp 150,000/family/month (USD 10.54/family/month) is done to meet food needs, and the addition of types of food commodities and freedom in the selection of commodities exchanged to improve nutrition and reduce stunting in poor households (Coordinating Ministry on Human Development and Culture, 2019).

3. Methodology

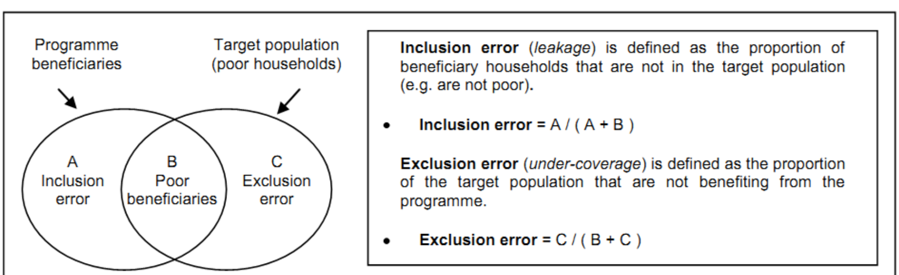
This research is a quantitative study using raw data from a survey of SUSENAS in March 2020 conducted by Statistics Indonesia (BPS). In addition, the researchers use several regional socio-economic indicators obtained from BPS publications. The data are at the provincial level.

To analyze the data, the research employs descriptive and inferential analysis. The descriptive analysis aims to explain the success of the Sembako Program to meet the targets. Meanwhile, inferential analysis is conducted using multilevel binary logistic regression. This analysis is used to find out besides household conditions, whether regional conditions also affect the implementation of the Sembako Program considering the Indonesian government implements regional autonomy.

Multilevel analysis is done to anticipate errors in the conclusion of a study with multilevel data (Hox et al., 2018). Multilevel analysis is done by analyzing multilevel data at their respective levels so that multilevel analysis is a suitable approach for analysis that considers social and individual contexts. In multilevel analysis, bound variables are at the lowest level while free variables can be defined at any level (Snijders & Bosker, 1999). The multilevel analysis conducted in this study uses data at two different levels. The first is the household level; the second is the provincial level.

Targeting efficiency is the proportion between the number of poor households who receive program benefits and the total number of program beneficiary households. Targeting errors include beneficiaries who come from non-poor households (inclusion error) and poor households that do not receive the assistance (exclusion error) (Devereux et al., 2017).

Figure 1. Targeting Errors (Inclusion Error and Exclusion Error)



Source: Adapted from "Kenya OVC-CT Programme Operational and Impact Evaluation - Baseline Survey Report", OPM 2008.

Source: Hurrell et al. (2011)

From figure 1, based on the targeting efficiency theory put forward by Coady and Skoufias (2004), targeting is said to be on target if the beneficiaries of the Sembako Program are poor households. Thus, the target accuracy rate is formulated as follows:

$$target\ accuracy\ rate = \frac{B}{A+B} \times 100\% \tag{1}$$

Calculation of targeting error rates in both exclusion error and inclusion error refers to the formula submitted by Cornia and Stewart (1993) in Stoeffler et al. (2016) as follows:

$$exclusion\ error\ rate = \frac{C}{B+C} \times 100\% \tag{2}$$

$$inclusion\ error\ rate = \frac{A}{A+B} \times 100\% \tag{3}$$

The target of the Sembako Program is 15.6 million low-income families or 25 percent of families with the lowest socio-economic conditions spread throughout Indonesia (Directorate of State Budget Preparation & Directorate General of Budget, 2020). The target population (of poor households) is the 25 percent of households that have the lowest per capita expenditure from the SUSENAS raw data in March 2020 and others included in non-poor households. The total number of the Sembako Program beneficiary targets is calculated from the number of households that are Sembako Program recipients, as obtained from SUSENAS raw data in March 2020. Therefore, this study uses the assumption that the family was the same as the household.

This study uses two models, namely the exclusion error and inclusion error models. The unit of analysis for the exclusion error model is poor households (value 1 if households did not receive assistance and value 0 if households received assistance), while for the inclusion error model it is non-poor households (value 1 if households received assistance and value 0 if households did not receive assistance). Information about households receiving assistance was obtained from SUSENAS raw data in March 2020 through the question of whether the household received the Sembako Program.

Each model had 12 independent variables. Then, the independent variables were grouped into two levels, namely the household level and the provincial level. The use of variables at the household level was because their socio-economic conditions determined households that received the food assistance. Variables at the provincial level were used to determine the role of social conditions of the region towards the occurrence of inaccuracies in targets, both exclusion and inclusion errors.

Table 1. Definition and Category of Independent Variables

Variables	Definition	Category
(2)	(3)	(4)
Household Factor		
Household Members	The number of household members.	Numeric
Marital Status of the Head of the Household	The marital status of the head of the household.	Single, Married, and Divorced
Gender of the Head of the Household	The binary of gender of the head of the household.	Man and Woman
Age of Head of Household	The age of the head of the household.	Numeric
Legal Identity Ownership	The binary of legal identity ownership the head of the household and/or his partner.	Yes if available and Not if not available
Savings Ownership	The binary of savings ownership in the household.	Yes if available and Not if not available
Disability	The binary of disability/the presence of disabled household members.	Yes if available and Not if not available
House Ownership	The binary of house ownership in the household.	Yes if available and Not if not available
Asset Ownership	The binary of asset ownership in the household.	Yes if available and Not if not available
Regional Contextual Factors		
Poor Population (000)	The number of poor population in the province.	Numeric
Gini Ratio	Gini ratio divided into low and medium.	Low if less than 0.4 and Medium if 0.4 and more

Regional Income	Regional income is divided into low, medium, and high based on percentile.	Low if less than Rp 6 triliun, Medium if Rp 6 – 14 triliun, High if more than Rp 14 triliun

The variables used in this study are based on the variables used to create the PMT model. These variables include per capita expenditure used to determine the poverty of households; demographic conditions of the household, including gender of the head of the household, the number of household members, the age of the head of household, the age of household members, the marital status of the head of the household, and the number of household members with a certain age range; education; home facilities that include the status of house ownership and the condition of the house; and ownership of assets (National Team to Accelerate Poverty Reduction, 2015).

In addition, the selection of variables is based on the theory of poverty put forward by several experts including Haughton and Khandker (2009) who said that a person is said to be poor if his income or consumption is still below the minimum limit specified. According to Ravallion (1992), the most important thing in measuring poverty is not only depending on consumption but opportunities for consumption. In addition to income, wealth is also a measure of consumption opportunities. Wealth can be both assets and savings. Sen (1983) said that poverty is related to a person's ability to meet his standard of living. These abilities are related to gender, age, and disability.

Variables at the provincial level were selected based on the theory presented by Coady et al. (2004) that areas with high incomes will have better ability in the implementation of programs, including poverty reduction programs. Targeting performance is better in areas with higher inequality. With high inequality, it will be easier to identify poor beneficiaries.

The sample used in the exclusion error model is poor households while the inclusion error model is non-poor households so the minimum, maximum, and average values of each model can be different (Table 2).

Table 2. Summary descriptive of dependent and independent variables

Variables	Poor Households			Non-poor Households		
	Min	Max	Mean	Min	Max	Mean
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable						
Sembako Beneficiary	0	1	0.73	0	1	0.11
Independent Variable						
Household Members	1	26	4.52	1	24	3.5
Marital Status of the Head of the Household	0	2	0.86	0	2	1.14
Gender of the Head of the Household	0	1	0.86	0	1	0.16
Age of Head of Household	13	97	49.53	11	97	48.97
Legal Identity Ownership	0	1	0.04	0	1	0.97
Savings Ownership	0	1	0.89	0	1	0.07
Disability	0	1	0.52	0	1	0.3
House Ownership	0	1	0.88	0	1	0.17
Asset Ownership	0	1	0.92	0	1	0.04
Poor Population (000)	51.79	4419.1	1748.78	51.79	4419.1	1418.01
Gini Ratio	0	1	0.90	0	1	0.9
Regional Income	0	2	0.98	0	2	1.38
Observations		85,633			248,596	

Source: Author calculation based on SUSENAS data in March 2020; Statistics Indonesia (2020b); Statistics Indonesia (2020c); Statistics Indonesia (2020d)

4. Results

4.1 The Success of the Sembako Program

One of the critical aspects in evaluating poverty reduction programs is the accuracy of the program targets. A higher target accuracy means more poor households will receive assistance. As a result, the government's goal to eradicate poor households will be more easily achieved. In Indonesia, the level of target accuracy of the Sembako Program was only 47.46 percent (Table 3).

Table 3. Success Rate of Targeting the Basic Food Program (percent)

Area Status	Target Accuracy Rate	Exclusion Error Rate	Inclusion Error Rate
(1)	(2)	(3)	(4)
Urban	44.82	73.93	55.18
Rural	49.18	69.01	50.82
INDONESIA	**47.46**	**71.04**	**52.54**

Source: Author calculation based on SUSENAS data in March 2020

Table 4. Summary Statistics on Poverty Rate, Poor Population, Gini Ratio, Regional Income, Exclusion Error Rate, and Inclusion Error Rate by Province

Province	Poverty Rate (%)	Poor Population (000)	Gini Ratio	Regional Income	Exclusion Error Rate (%)	Inclusion Error Rate (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sumatra						
Aceh	14.99	814.91	low	medium	61.73	63.86
North Sumatera	8.75	1,283.29	low	medium	76.61	66.97
West Sumatera	6.28	344.23	low	medium	75.14	75.7
Riau	6.82	483.39	low	medium	81.51	76.28
Jambi	7.58	277.80	low	low	84.29	61.38
South Sumatra	12.66	1,081.59	low	medium	80.43	52.47
Bengkulu	15.03	302.58	low	low	68.37	62.26
Lampung	12.34	1,049.32	low	medium	70.87	50.29
Bangka Belitung Islands	4.53	68.40	low	low	80.26	95.53
Riau Islands	5.92	131.97	low	low	79.85	79.47
Java						
DKI Jakarta	4.53	480.86	low	high	87.48	91.82
West Java	7.88	3,920.23	medium	high	73.47	51.88
Central Java	11.41	3,980.90	low	high	65.34	46.36
DI Yogyakarta	12.28	475.72	medium	low	53.86	48.46

East Java	11.09	4,419.10	low	high	68.61	45.82
Banten	5.92	775.99	low	medium	73.11	71.29
Bali & Nusa Tenggara						
Bali	3.78	165.19	low	medium	77.95	59.88
West Nusa Tenggara	13.97	713.89	low	low	63.07	52.8
East Nusa Tenggara	20.90	1,153.76	low	low	63.6	33.85
Kalimantan						
West Kalimantan	7.17	366.77	low	low	82.8	62.46
Central Kalimantan	4.82	132.94	low	low	87.78	78.91
South Kalimantan	4.38	187.87	low	medium	73.43	66.63
East Kalimantan	6.10	230.27	low	medium	69.06	86.09
North Kalimantan	6.80	51.79	low	low	71.27	87.54
Sulawesi						
North Sulawesi	7.62	192.37	low	low	72.98	54.47
Central Sulawesi	12.92	398.73	low	low	73.73	53.39
South Sulawesi	8.72	776.83	low	medium	74.93	40.16
Southeast Sulawesi	11.00	301.82	low	low	72.31	44.58
Gorontalo	15.22	185.02	medium	low	61.14	39.41
West Sulawesi	10.87	152.02	low	low	74.12	29.63
Maluku & Papua						
Maluku	17.44	318.19	low	low	73.29	59.53
North Maluku	6.78	86.37	low	low	94.17	79.11
West Papua	21.37	208.58	low	medium	90.42	81.6
Papua	26.64	911.37	low	medium	98.74	59.09
INDONESIA	**9.78**	**26,424.02**	low		71.04	52.54

Source: Author calculation based on SUSENAS data in March 2020; Statistics Indonesia (2020b); Statistics Indonesia (2020c); Statistics Indonesia (2020d)

Targeting the Sembako Program was carried out using PMT and a community-based model. The purpose was to gather real poor households (Alatas et al., 2012). Even so, inaccuracies were still found in targeting non-poor households that received the Sembako Program (inclusion error) and poor households that did not receive the Sembako Program (exclusion error). The number of households in the exclusion errors was much larger than the target accuracy. The rate of exclusion errors reached 71.04 percent, while the inclusion error was only 52.54 percent (Table 3.). Indeed, accuracy is one of the challenges in targeting. Although it is almost impossible to have 100 percent target accuracy (Devereux et al., 2017), the government should still pay close attention to the high number of mistargeting compared to target accuracy.

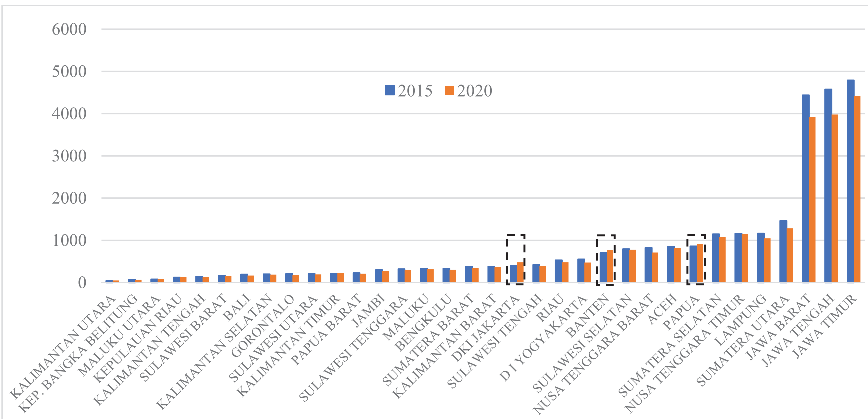
The high rate of exclusion error that occurs in eastern Indonesia such as Papua, North Maluku, and West Papua Province (Table 4) occurs due to infrastructure limitations for the implementation of the Sembako Program (Kamil, 2020). These limitations cause the Sembako Program has not been implemented in 23 districts in Papua Province, 5 districts in West Papua Province, and 2 districts in North Maluku Province.

High inclusion error rates occur in Bangka Belitung Islands Province and DKI Jakarta (Table 3). As a province with an archipelago, it is a challenge for the local government of Bangka Belitung Islands Province to coordinate in running various government programs including the Sembako Program so that the inclusion error rate becomes high. DKI Jakarta is the capital of the Republic of Indonesia which has a high migration rate which causes faster beneficiary households to change so that the inclusion error rate becomes high (Statistics Indonesia, 2016a).

Several factors caused the high rate of target inaccuracy in the Sembako program. One possible factor was that the Sembako Program's beneficiary database was outdated (Sumarto, 2021). The Sembako Program database was called UDB. The database was last updated in 2015 through the PBDT. Many Indonesian people are vulnerable to poverty (World Bank, 2006). With a time difference of more than five years, there could be changes in conditions or poverty rates in Indonesian households. Improvement of poverty data needs to be done continuously, considering that poverty is dynamic and changes over time (National Team to Accelerate Poverty Reduction, 2015).

Some families were once considered poor but are no longer, and vice versa. During the four years (2011-2015), 14 percent of households were lifted out of poverty, while 16 percent fell into it (Adani & Maulana, 2019). Although the total number of poor people in Indonesia has decreased, several provinces experience an increase in the number of poor people including DKI Jakarta, Banten, and Papua (Figure 2).

Figure 2. Number of Poor People by Province, 2015 and 2020 (in thousands)



Source: Statistics Indonesia (2016b); Statistics Indonesia (2020b)

Inaccuracy in the recipient database makes the recipient coverage less comprehensive and excessive. Consequently, the target is inaccurate, namely exclusion and inclusion errors (World Bank, 2006). In addition, according to Sutanto et al. (2020), the occurrence of inclusion errors in food assistance programs stems from regional leaders who are reluctant to face data conflicts on the ground. As a result, people who should not be entitled to receive assistance are included as beneficiaries.

Table 5. Recipients of the Sembako Program by Percapita Expenditure Decile in Indonesia, 2020 (percent)

Percapita Expenditure Decile	Receive	Do Not Receive
(1)	(2)	(3)
Decile 1	32.94	67.06
Decile 2	27.35	72.65
Decile 3	23.63	76.37
Decile 4	19.32	80.68
Decile 5	16.03	83.97
Decile 6	13.32	86.68
Decile 7	10,17	89.83
Decile 8	5.98	94.02
Decile 9	2.95	97.05
Decile 10	0.84	99.16

Source: Author calculation based on SUSENAS data in March 2020

The Indonesian government aims for as many as 15.6 million poor households to receive the program. This rate is approximately 25 percent of total households in Indonesia. Table 5 provides a summary of who is entitled to receive assistance. According to the per-capita expenditure decile, the beneficiaries should only be in deciles 1, 2, and 3. However, the table shows that the beneficiaries of the Sembako Program also came from higher deciles. The wealthiest households were even listed as receiving assistance indicated by the per capita expenditure in the highest decile, which was 0.84 percent. Conversely, some of the poorest households (67.06 percent), as noted in the lowest per capita expenditure decile, did not receive the Sembako Program.

4.2 Determinants Exclusion Error and Inclusion Error

The low level of targeting accuracy compared to the inaccuracy of targets, both exclusion and inclusion errors, is interesting to study. One of the factors that cause inaccuracy of targets is a limited administrative capacity that makes the database of the Sembako Program recipients outdated (Alatas et al., 2019; Sumarto, 2021). Determining the target recipients of poverty reduction programs, including the Sembako Program, requires understanding why the household is poor. Therefore, complete information is needed about the socio-economic conditions of the household (Haughton & Khandker, 2009). The target should be households with the lowest income, but this information is difficult to obtain (Alatas et al., 2012). Although they aim to reduce poverty, poverty reduction programs, including the Sembako Program, are not only delivered to poor households but also vulnerable poor households who have limitations to meet their daily needs, including the elderly, orphans, and persons with disabilities (Devereux et al., 2017; Coordinating Ministry on Human Development and Culture, 2019). In addition to that, regional inequality and local governments' uneven capacity are also other obstacles for poverty reduction (World Bank, 2006). The success of targeting depends on the capacity of the local governments in implementing poverty reduction programs (Devereux et al., 2017). The capacity includes regional income, government accountability, and income inequality. Regions with low regional income and income inequality tend to fail to implement the programs well (Coady et al., 2004; Devereux et al., 2017).

For those reasons, the present research uses a multilevel binary logistic regression analysis. The analysis was carried out to determine household characteristics and the role of the regional socio-economic conditions that allowed the occurrence of inaccuracies in the target, both exclusion and inclusion errors. The results are presented in Table 6.

The determinants of beneficiary households used in this study are mostly the same as the variables used for the calculation of PMT of the household beneficiary of UDB. The results obtained the majority following the theory used. Poor households with male heads of households, younger heads of households, no legal identity, no disabled household members, and having assets, have a greater chance to become exclusion error. Legal identity ownership variables have the greatest effect compared to other independent variables as household factors. Poor households that do not have a legal identity, have a greater tendency of 1.96352 times to be exclusion error compared to poor households that have a legal identity. Then, poor households that have assets have a greater tendency 1.59072 times to be exclusion error than poor households that do not have assets. The regional contextual factor that has the greatest effect is the Gini ratio. Poor households living in areas with a low Gini ratio have a greater tendency to become exclusion errors.

Table 6. Multilevel Binary Logistics Regression Results

Variables	Exclusion Error			
	P-value Wald	Odds Ratio	P-value Wald	Odds Ratio
(1)	(2)	(3)	(4)	(5)
Household Factor				
Household member	0.000 *	0.90674	0.000*	
Marital Status of the Head of the Household				
Divorced	*Reference Category*		0.000*	0.000 *
Married	0.000 *	0.85364	0.000*	0.000 *
Single	0.326 **	1.09516	*Reference Category*	
Gender of the Head of the Household				
Woman	*Reference Category*		0.000*	1.22605
Man	0.007 *	1.10842	*Reference Category*	
Age of Head of Household	0.000 *	0.98985	0.000*	1.01092
Legal Identity Ownership				
Yes	*Reference Category*		0.000*	2.23934
Not	0.000 *	1.96352	*Reference Category*	
Savings Ownership				
Not	*Reference Category*		0.000*	1.06409
Yes	0.000 *	0.41658	*Reference Category*	
Disability				
Yes	*Reference Category*		0.000*	1.29246
Not	0.000 *	1.17054	*Reference Category*	
House Ownership				
Not	*Reference Category*		0.000*	0.79127
Yes	0.000 *	0.66960	*Reference Category*	

Asset Ownership				
Not	*Reference Category*		0.000*	1.99950
Yes	0.000 *	1.59072	*Reference Category*	
Regional Contextual Factors				
Number of Poor Population	0.000 *	0.99932	0.000*	1.00024
Gini Ratio				
Medium	*Reference Category*			
Low	0.002 *	1.57193	0.171***	0.78614
Regional Income				
High	*Reference Category*			
Medium	0.000*	0.12675	0.002*	1.66442
Low	0.000*	0.09818	0.000*	2.11412
Observation	**85,633**		**248,596**	

Note: * significant at the 5 % significance level,** not significant

Source: Author calculation based on SUSENAS data in March 2020; Statistics Indonesia (2020b); Statistics Indonesia (2020c); Statistics Indonesia (2020d)

Non-poor households with more household members, female heads of households, older heads of households, the presence of disabled household members, having a legal identity, and no assets, have a greater chance to become inclusion error. Legal identity ownership is also the variable that has the greatest effect on the inclusion error model. By having a legal identity, non-poor households are more likely to be an inclusion error 2.23934 times than non-poor households that do not have a legal identity. Different from the exclusion error model, in the inclusion error model the marital status variable has a significant effect. Non-poor households with divorced household heads were 2.22393 times more likely to be inclusion errors compared to non-poor households with single heads of households. While those who are married are more likely 2.22393 times to be an inclusion error compared to the head of a single household. Non-poor households that do not have assets are 1.99950 times more likely to be inclusion errors than non-poor households that have assets.

The regional contextual factor that has the greatest effect on the inclusion error model is the regional income. Households living in areas with low regional incomes were 2.11412 times more likely to be inclusion errors than households living in areas with high regional incomes. Meanwhile, those living in areas with medium regional incomes are 1.66442 times more likely to be inclusion errors than in areas with high regional incomes.

The conformity of the results of this study with the variables used in the calculation of PMT indicates that the PMT formula used for targeting the Sembako Program is acceptable in identifying poor households.

5. Discussion

Poverty reduction programs not only target poor households but also those who are vulnerable to poverty, such as the elderly, orphans, and people with disabilities (Devereux et al., 2017; Stoeffler et al., 2016). These limitations make households with the elderly as the household head and the presence of people with disabilities have higher opportunities to receive the Sembako Program (Gundersen & Oliveira, 2001; Stoeffler et al., 2016; Sutanto et al., 2020). According to World Bank (2006), this group is more prone to become poor because, when a shock occurs, the vulnerable group is even more affected.

According to Gundersen and Oliveira (2001), households led by married couples have a greater chance of participating in poverty reduction programs. Another factor that can be used in targeting poverty reduction programs is the number of dependents in the household. Those who have many dependents increase the probability of becoming the beneficiary of the poverty reduction program (Alatas et al., 2012; Stoeffler et al., 2016). Households with a married head of household have the most household members compared to those with unmarried status (Table 7). Thus, it makes households with married heads of household have a greater chance of receiving the Sembako Program. This finding corroborates Skoufias et al.'s (2001) study, which claims that exclusion errors occur in small households while inclusion errors occur in large households, especially with many children.

Table 7. Average Number of Household Members by Marital Status of the Head of the Household

Marital Status of the Head of the Household	Poor Households	Non-poor Households
(1)	(2)	(3)
Single	2.92	1.53
Divorced	3.47	2.62
Married	4.51	3.83

Source: Author calculation based on SUSENAS data in March 2020

Another interesting finding was that households whose head was female had a greater chance of receiving the Sembako Program. Some reports suggest that households with a female head are likely to be poorer than those with a male head (Asian Development Bank, 2006). The reason is the fact that men's income is higher than that of women. Hence, households with a female head become one of the poverty reduction program targets. To this extent, inclusion error increases for households with a female household head (Haughton & Khandker, 2009; Kusumawati & Kudo, 2019; Stoeffler et al., 2016).

To receive food assistance, the beneficiary should create a bank account. To do so, they must provide an identity card (Coordinating Ministry on Human Development and Culture, 2019). Kusumawati and Kudo (2019) argue the importance of having an identity card to claim government programs, like the Sembako Program. In addition to errors in determining program recipient databases, exclusion errors can also be caused during the program's execution. The absence of an identity card increases the chances of poor households not receiving the food assistance program (Harbitz & Tamargo, 2009). It also explains why poor households with no identity cards had a lower chance of receiving the Sembako Program (Kusumawati & Kudo, 2019).

Savings is one way to survive economic shocks to prevent falling into poverty (World Bank, 2006). However, from the SUSENAS data, it turned out that saving was negatively related to poor households' probability of receiving the Sembako Program. Households that had savings tended to have a greater chance of receiving the Sembako Program. One possible reason was that households with savings turned out to have more average number of household members (3-5 people) than not having savings (2-4 people). The large number of household members that must be borne made households with savings even more likely to receive the Sembako Program. Unfortunately, the amount of savings in the SUSENAS March 2020 was not asked, so there was no information about the amount of savings owned by the household.

Gundersen and Oliveira (2001) stated that households with houses tend not to participate in food assistance programs. However, the SUSENAS obtained that households that own a house have a greater chance of receiving the Sembako Program. The house variable used in this study is only limited to ownership without looking at the quality of the house. Research conducted by Stoeffler et al. (2016) concluded that the exclusion error is lower in households that do not have solid roofs and walls. Thus, homeownership alone cannot be used as a basis for determining poor households. It is also necessary to look at the condition or quality of the house, both area, walls, floors, roofs, and the likes to truly determine the condition of household poverty.

Table 8. Number of Households by Status of Residential Area (%)

House Ownership	Poor Households		Non-poor Households	
	Yes (%)	Not (%)	Not (%)	Not (%)
(1)	(2)	(3)	(4)	(5)
Residential Area Status				
Urban	78.7	21.3	71.6	28.4
Rural	91.9	8.1	91.4	8.6

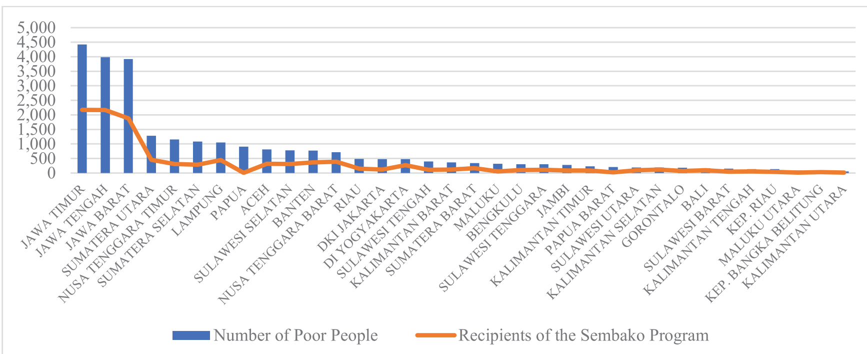
Source: Author calculation based on SUSENAS data in March 2020

Table 8 illustrates that for both poor and non-poor households, home-ownership among rural households is higher relative to their urban counterparts. At the same time, according to Statistics Indonesia (2020b), the poverty rate in rural areas is higher than in urban areas. As it turns out, the percentage of households occupying habitable homes in urban areas (63.24 percent) is more than in rural areas (54.82 percent) (Statistics Indonesia, 2020f). This means that although more rural households have their own homes, more are less livable. This condition makes the households that have a house have a bigger chance to get the Sembako Program.

Assets owned by poor households can help them get out of poverty because they can use these assets to meet their daily needs (Haughton & Khandker, 2009). The assets in this study referred to having a gas cylinder of 5.5 kilograms or more, refrigerators/refrigerators, air conditioners, water heaters, home telephones, computers/laptops, gold/jewelry (minimum 10 grams), motorcycles, boat, motorboat, car, flat-screen television (minimum 30 inches), and land. Thus, households with assets have a lower chance of accepting the Sembako Program, as shown in Stoeffler et al.'s (2016) research.

Ravallion (1992) and Wardhana (2020) suggest that differences in poverty conditions also determine the success of an area in poverty reduction efforts. In this study, the poverty condition of an area is approximated by the number of poor people residing in the area. A large number of poor people indicates the greater effort that the local government must make to decrease poverty, including the occurrence of targeting errors. However, this study suggests that the increasing number of poor people reduces the chances of exclusion errors and increases the chances of inclusion errors. As shown in Figure 3, the number of poor people correlates positively with the number of recipients of the Sembako Program. With so many beneficiaries, the chances of poor households not receiving the Sembako Program are getting smaller. This finding was also reported by Alatas et al. (2012) that areas with many poor households would have lower errors in targeting, especially the occurrence of exclusion errors. Instead, it tended to produce more inclusion errors than exclusion errors (Skoufias et al., 2001). Areas with a poorer population need to get more attention related to the possibility of inclusion error, supervision and assistance in the implementation of programs need to be tightened so that social assistance can be received by those who are entitled to receive it.

Figure 3. Number of Poor People and Recipients of the Sembako Program by Province in Indonesia, 2020 (in thousands)



Source: Author calculation based on SUSENAS data in March 2020; Statistics Indonesia (2020e)

Income inequality in this study was measured using the Gini ratio. The low Gini ratio indicates a greater risk of exclusion errors. These results are in line with the results of Coady et al. (2004). They argue that with high-income inequality, the difference between rich and poor is easier to identify. Thus, the targeting accuracy of poverty reduction programs is higher. In other words, determining poor households as targets for the program is easier so that exclusion errors are more likely to occur mostly in areas with low-income inequality.

According to Coady et al. (2004), regions with high incomes have a better ability to implement various programs, including poverty reduction programs. They are capable of directing appropriate beneficiaries. However, this study found that provinces with medium or low regional incomes have a lower probability of exclusion error than those with high regional incomes. The success of a region in achieving development targets depends on increasing the amount of expenditure or income and increasing services that can be received by development targets (World Bank, 2006). Increasing the amount of spending on social programs is not effective in reducing poverty. Such action is even considered counterproductive to reducing poverty (Chaudhuri et al., 2020; Sumarto et al., 2004). It means that high regional income alone is not enough to successfully implement the programs included in the Sembako Program successfully. Reducing the number of poor people through poverty reduction programs can be done better if the government enforces good governance and increases the capacity of local governments to deliver more effective public services (Chaudhuri et al., 2020; Sumarto et al., 2004). This idea was also conveyed by Devereux et al. (2017), where the success of targeting is determined by government accountability in the implementation of poverty reduction programs.

Non-poor households living in low-income areas have a greater probability of the inclusion error than households living in areas with high regional income. These results are following those presented by Coady et al. (2004). They believe that sizeable regional income leads the region to carry out many programs well, including achieving target accuracy. The success of targeting has to do with program design and implementation. Yet, good targeting design and implementation in poverty reduction programs require a large budget. Therefore, a high targeting administration cost is necessary to get a high level of targeting accuracy (Besley & Kanbur, 1990 cited in Devereux et al., 2017).

Indonesia's heterogeneous territory is divided into 34 provinces. Even with islands and regional autonomy implemented at the district level, implementing various government programs varies between regions. The availability of resources to fund public spending, the effectiveness of service delivery, the quality of governance, and the institutional capacity to implement different government programs between regions lead to the effectiveness of poverty reduction programs also differing between regions. The success of poverty alleviation in areas that already have a TKPKD office (the Regional Poverty Reduction Coordination Team) is better than areas that do not yet have a TKPKD office (Sumarto et al., 2014).

6. Recommendations

The low level of targeting accuracy compared to the inaccuracy of the Sembako program targets could be due to the lack of an up-to-date database of the recipients. For this reason, it is necessary to periodically update the database of the recipients of the Sembako Program and other social assistance to obtain a database with more up-to-date conditions so that the level of accuracy of the targets of the Sembako Program increases. In addition, there is a need for assistance and supervision during the program implementation to increase its success. Thus, increasing the targeting accuracy of the Sembako Program can increase the effectiveness of the Sembako Program, thereby reducing the poverty rate.

The main purpose of the Sembako Program is to overcome poverty in Indonesia. However, the high level of exclusion error in the Sembako Program can hamper the success of poverty reduction programs because poor households who should be able to get out of poverty with the help of the Sembako Program, become difficult to meet their needs because they do not get the Sembako Program. To be able to reduce poverty, poor households should not be missed from the distribution of aid.

To reduce the rate of exclusion error, the government must also pay attention to household conditions, especially with male, young, and single heads of households, and no disabled household members. The household is considered able to meet the needs of his life. However, it does not rule out the possibility that these households are poor households that must get food assistance programs. Moreover, the government should make it easier for poor households that do not have a legal identity to get food assistance programs. Although it does not have a legal identity, the household remains a part of the Indonesian population that is entitled to a food assistance program so that the poverty rate can be suppressed.

The inclusion error rate can be reduced if the government pays attention to households with female, old, and divorced heads of households. They are generally considered to be vulnerable households. However, many of them have good economic conditions so that they can meet their needs. Among them are retired civil servant or their spouses, so that even though women, old, and divorced status they still get a pension to meet their needs. These households should not need to get food assistance, so the government needs to add such information in determining the beneficiary household.

The magnitude of the opportunity for the head of a female household to become a recipient of the Sembako Program can be used as one of the factors in determining the household recipients of social assistance programs. Women as heads of households have a heavier burden than men, so female heads of households need to get more attention from the government, especially concerning social assistance programs.

Saving and home ownership cannot be used as an indicator of poor households. There needs to be more complete information related to the condition of the house and the amount of savings so that it can be used as an indicator of poor households.

The regional socio-economic conditions also contributed to the target inaccuracy of the Sembako program. Thus, interventions should address not only the household socio-economic conditions but also the socio-economic conditions of the region. Increasing regional revenues and improving regional institutions can be done to improve the implementation of central government programs including reducing exclusion error and inclusion error rate.

7. Conclusions

One critical aspect of identifying the effectiveness of the poverty reduction program is the accuracy of the target recipients of the program. A lower level of target accuracy than target inaccuracy in both inclusion error and exclusion error needs attention. The updating of the database of Sembako Program recipients that are carried out periodically and supervision of its implementation is expected to improve the accuracy of its targets.

The present research discovered the characteristics of poor households that do not receive the Sembako Program. The characteristics covered unmarried household heads, younger household heads, no identity cards, no disabled household members, and had assets. The opposite condition allowed non-poor households to become recipients of the Sembako Program, such as the household head was married, female gender, the age was older, had an identity card, a disabled household member, and no assets.

The characteristic of the region that allowed for a larger exclusion error was the low Gini ratio. Meanwhile, regional characteristics that allowed greater inclusion errors were the larger number of poor people and lower regional incomes. An increase in regional revenues can be done to increase the effectiveness of government programs.

Policies regarding the determination of beneficiary households can be improved by looking at the characteristics of poor households that do not receive the Sembako Program. That way, the exclusion error rate can be reduced so that poverty reduction programs can be more effective. In addition, efforts made by the government by increasing revenues and strengthening institutions can encourage the implementation of government programs better.

The limitation of the present study is that the existing data only use those at the provincial level. Regional autonomy implemented in Indonesia makes the municipality the holder of authority/power. Therefore, further research that involves data from the municipalities is highly suggested to provide a more significant contribution than the provincial data.

This study uses cross-sectional data on conditions conducted in March 2020, so that the results of the study obtained can only describe the conditions of the year. That way, researchers could not compare the results of this study with the conditions of previous food assistance programs.

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