Available online at http://journals.ums.ac.id, Permalink/DOI: 10.23917/jep.v26i1.10693

Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi dan Pembangunan, 26 (1), 2025, 1-20

Evidence on the Beneficial Impact of Food Voucher Programs in Java Island

Nur Afini Muliandari[1], Rus'an Nasrudin[2]
[1,2]Faculty of Economic and Business, University of Indonesia
Corresponding Author: nur.afini11@ui.ac.id

Received: April 2024 | Revised: October 2024 | Accepted: May 2025

Abstract

This study aims to compare the effects of two food voucher programs on household welfare in Indonesia, namely the BPNT and Sembako Program, focusing on Java Island. It uses household food expenditure share (FES) and household dietary diversity score (HDDS) as outcome variables representing household welfare. This study utilizes the 2017–2021 cross-sectional data from the National Social Economic Survey (SUSENAS) published by the Central Bureau of Statistics. The Propensity Score Matching (PSM) and Ordinary Least Squares (OLS) methods were employed. The main estimate employs a multi-arm treatment approach to compare both programs to a common control group. By conducting PSM, this study controls about 76 observed characteristics of households. In addition, this method introduces time-variant and time-invariant fixed effects in the OLS estimation. The results show that the BPNT and Sembako Program decrease household FES and increase HDDS. The food voucher programs have different effects across provinces in Java, with food voucher programs tending to have greater effects in provinces with lower initial levels of welfare. Notably, the higher flexibility of the food voucher in the Sembako Program yields a greater effect on households. The higher flexibility of the food voucher allows beneficiaries to choose their food items other than rice and eggs. Thus, in addition to being effective in reducing FES, the Sembako Program is more effective in increasing HDDS. The policy implications directed at the government can improve targeting accuracy, voucher value, and infrastructure for accessing food vouchers, in alignment with the objectives set for the program.

Keywords: Food Voucher, Welfare, Java, Multi-arm Intervention
JEL classification: I38, Q18, C01

How to Cite: Muliandari N. A., Nasrudin R. (2025). Evidence on the Beneficial Impact of Food Voucher Programs in Java Island, *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi dan Pembangunan,* 26(1), 1-20. doi: https://doi.org/10.23917/jep.v26i1.10693

1. INTRODUCTION

Food security has been a central focus of national development in Indonesia since its independence, with self-sufficiency in key agricultural products being a major political objective. Food is one of the most essential basic human needs, and its fulfillment is a fundamental aspect of human rights, as guaranteed by Law No. 18 of 2012 concerning Food, which is essential for the development of qualified human resources. Comprehensive food security encompasses four primary dimensions: food availability, food accessibility, food stability, and food utilization, each intricately linked and influenced by a spectrum of economic and non-economic factors (Abdulai & Kuhlgatz, 2011).

The implementation of food voucher policies represents a crucial intervention in addressing global food security concerns (Bizikova et al., 2020). Beyond its immediate impact on alleviating hunger, these policies have the potential to significantly influence dietary diversity—a key component of overall nutritional well-being. Understanding the relationship between food voucher and dietary diversity is paramount in shaping effective policy design that not only ensures access to food but also promotes balanced and nutritious diets. Indonesia is among the countries that have adopted food intervention policies in various forms, with the latest being known as the Sembako Program (Dewi & Pangaribowo, 2022). Nevertheless, empirical research on the effects of this recent program on food diversity remains limited.

The Sembako Program constitutes a pivotal component of Indonesia's evolving social assistance initiatives aimed at providing food subsidies. It is one of the various food assistance programs that the government has been implementing since 1998, following a series of policy changes (Sadono, 2018). Since 2017, the food assistance distribution mechanism has shifted to non-cash assistance through food voucher. This began with the BPNT program, where food voucher could be used to purchase rice and eggs. The transition to a non-cash distribution mechanism is seen to improve the effectiveness of food assistance delivery and increase protein intake from eggs in beneficiaries (Banerjee et al., 2023; Hermawan et al., 2021; B. Rachman et al., 2018). Following BPNT's expansion to nationwide beneficiaries, the government enhanced the program by increasing the benefit amount and the range of commodities, renaming it the Sembako Program in late 2019, while retaining its targeting and mechanisms. However, empirical studies comparing whether the expansion of non-cash food assistance benefits leads to improved household welfare and dietary diversity remain scarce.

The Sembako Program's key feature is the expansion of both benefit amounts and food items compared to the BPNT Program, and it is expected to further enhance household dietary diversity. The program provides beneficiaries with a broader choice of food commodities, beyond just rice and eggs. Thus, the goal of the Sembako Program is not only to fulfill food consumption quantity but also to improve dietary diversity and nutritional intake. A limitation of previous studies is the lack of research comparing the interaction between the BPNT and Sembako Program on household FES and HDDS simultaneously. The purpose of this study is to estimate the relative impact of the Sembako Program on beneficiaries' welfare, compared to its predecessor, the BPNT Program. The analysis uses household data from Java Island as the sample, due to its status as the most populous island and its relatively better access to non-cash infrastructure compared to other islands. However, Java Island still experiences welfare inequality.

This study offers several novelties. First, related studies have primarily focused on the impact of food voucher programs on household conditions (Banerjee et al., 2023; Hidayat et al., 2022; Hidrobo et al., 2014; Savy et al., 2020; Zaki & Sulistyaningrum, 2021). Therefore, this study fills a gap by comparing the impact of two types of food voucher programs on household conditions simultaneously. Second, another novelty of this study is the use of repeated cross-sectional data. We employ PSM separately for each year to create pseudo-randomization before estimating the impact of both food voucher programs.

To address the gaps in previous research, this study will compare the impact of the BPNT and Sembako Program on beneficiaries' Food Expenditure Share (FES) as a measure of welfare and on the Household Dietary Diversity Score (HDDS). To compare the impact of both food voucher programs, we employ a multi-arm approach with Propensity Score Matching (PSM) as our pre-estimation method to create a common control group.

2. RESEARCH METHODS

2.1. Data

This study utilizes secondary data obtained from the Central Bureau of Statistics, specifically employing pooled cross-sectional data from SUSENAS 2017 to 2021. The analysis focuses on households located in Java, the most populous island in Indonesia. According to the 2020 Census, Java is home to 56.01% of Indonesia's total population of 272 million people. Java was chosen due to its status as a center of development, with adequate non-cash access and facilities. Additionally, many of the pilot areas during the initial implementation of BPNT were in Java. However, it is important to note that Java still grapples with issues of inequality, contributing to rising levels of poverty, food insecurity, and obesity among the lower segments of the economy (Elmes, 2018; Setiawan et al., 2020). Rahayu et al. (2019) also found inequality in food security status across provinces in Java.

The data utilized in this research were collected from the SUSENAS modules, which included both household and individual data. The individual module provides sociodemographic

information, which will be used to predict household eligibility for receiving food assistance programs based on propensity scores. The household consumption module includes consumption expenditure details, which will be used to measure the Household Food Expenditure Share (FES) and Household Dietary Diversity Score (HDDS).

Table 1 Food Groups

No	Food Group	Code of the Commodities by National Socioeconomic Survey	
		2017	2018-2021
1	Rice	Code 2-9	Code 2-7
2	Tubers	Code 11-19	Code 9-15
3	Seafood	Code 21-55	Code 17-51
4	Meat	Code 57-75	Code 53-61
5	Eggs and Milk	Code 77-89	Code 63-71
6	Vegetables	Code 91-119	Code 73-97
7	Legumes	Code 121-131	Code 99-105
8	Fruits	Code 133-154	Code 107-119
9	Oil and Coconut	Code 156-161	Code 121-124
10	Beverages	Code 163-172	Code 126-132

Table 1. (continued)

No	Food Group	Code of the Commodities by National Socioeconomic Survey	
		2017	2018-2021
11	Spices	Code 174-182	Code 134-145
12	Other Foods	Code 187-195 and Code 197-228	Code 147-150 and Code 152-181

Source: SUSENAS 2017-2021

The researchers analyzed household data from Java, encompassing 96,174 households in 2017, 95,885 households in 2018, 96,751 households in 2019, 102,451 households in 2020, and 105,110 households in 2021. Using the consumption module, the researchers categorized these households into twelve food groups, as detailed in Table 1. Processed foods were included within the various food groups, whereas alcoholic beverages were excluded from the estimation of HDDS.

Although this study is based exclusively on household data from Java, it acknowledges the potential for regional variations in food prices over the years. Given that the SUSENAS dataset does not provide specific food prices, the researchers calculated the food price per unit by dividing weekly household food expenditure by weekly household food consumption. The researchers then aggregated these unit prices to determine the total food expenditure for each district on an annual basis. To address regional price disparities, the researchers applied the Laspeyres price index methodology, as used by Kronebusch & Damon (2019), which employs a reference state to control for price differences. In this research, the researchers used the Laspeyres price index formula to construct the food price index at the district level, dividing the total food expenditure in each district annually by the total food expenditure in each district for the base year of 2017.

Social safety net programs in developing countries often use proxy means-testing, as many potential beneficiaries are employed in the informal sector and lack verifiable income recordse (Alatas et al., 2012). Proxy means testing typically relies on extensive, periodic quasi-censuses of the population. Governments use household assets or per-capita consumption to estimate incomes. Consequently, in this research, eligibility for benefits is determined by predicted income, which is approximated through the analysis of 76 covariates. These covariates include the age, gender, marital status, education, and occupation of the household head; household size, dependency ratio, and educational attainment within the household; housing status and characteristics, drinking water source, toilet facility, sewage facility, and lighting source; asset ownership; and other social protection programs affecting household food insecurity (Ardianti & Hartono, 2022; Hanna & Olken, 2018).

2.2. The Econometrics Techniques

To evaluate the impact of the Sembako Program on household food expenditure, the researchers employed a quasi-experimental methodology combining propensity score matching (PSM) and ordinary least squares (OLS) regression. PSM was used as a pre-estimation step to create counterfactuals based on 76 observed characteristics, thus mitigating selection bias arising from non-randomization (Austin, 2011).

Given the availability of repeated cross-sectional data, the researchers conducted PSM separately for each year from 2018 to 2021 to ensure contemporaneous control. For the pre-treatment period in 2017, the researchers designated the lowest 10% of per-capita expenditure as a control group. TNP2K defines a proxy means-test (PMT) score cut-off of 30% as strongly associated with eligibility for food assistance programs. Thus, a lower cut-off indicates a higher likelihood of household eligibility for receiving food assistance.

The researchers used kernel-based PSM, which has been shown to outperform one-to-one propensity score matching, regardless of the number of potential controls available (Berg, 2011). The assumption underlying kernel matching and caliper matching are slightly different. With kernel matching, the more "similar" the untreated observations are to the treated observations, the more weight they are given. With caliper matching, all untreated observations within the specified radius of the treated observation are used, and they all receive the same weight (Caliendo & Kopeinig, 2008). Kernel matching is more effective in reducing the mean standardized difference while preserving almost all observations from the original sample, compared to caliper matching. Kernel weighting also achieved the best covariate-specific balance between the treatment and comparison groups. Kernel matching assigns greater weight to better matches, thus maximizing precision while retaining sample size without exacerbating bias (Garrido et al., 2014). The pre-estimation model used in this research is specified in equation (1) and (2). The main estimation using OLS with multi-arm approach is specified in equation (3):

$$W\mathrm{h} = \mathrm{W}\big(\mathrm{Pr}(\mathrm{X_h}\,)\big) = W(\mathrm{Pr}(FV\mathrm{h} = 1 \mid X\mathrm{h}\,))S\mathrm{h} = 1 \tag{1}$$

$$\beta_{psm} = E(Y_h|FV_h = 1,\, S_h = 1) - E(W_h(Y_h|FV_h = 0,\, S_h = 1)) \tag{2}$$

$$\mathrm{Yhrt} = \beta_0 + \beta_{1BPNT}\mathrm{hrt} + \beta_{1Sembako}\mathrm{hrt} + \alpha Z_{rt} + v_t + u_r + \delta_{rt} + \varepsilon,\ (\mathrm{W}\big(\mathrm{Pr}(\mathrm{X_h}\,)\big) \text{ x fwt}) \tag{3}$$

Where W_h is weight for household h based on propensity score $Pr(X_h)$. X_h is vector covariates for household h in each year, to predict the probability of household h on receiving food voucher (FV_h). $S_h = 1$ represents the on-support range for household h in the treatment and control groups that will be matched based on W_h. PSM will automatically estimate treatment effect β_{psm} based on differences in expected outcome $E(Y_h)$ of household h in the treatment group ($FV_h = 1$) and control group (W_h ($FV_h = 0$)) in terms of matched samples in the on-support range. Y_{hrt} is dependent variables (FES & HDDS) of household h in region r at time t. β_1 is the marginal change compared to the control group, of being in the treatment. Our treatment variables $BPNT_{hrt}$ and $Sembako_{hrt}$ have binary values of 1 if the household h in region r at time t receives BPNT or the Sembako Program, and 0 otherwise. αZ_{rt} is a vector of regions and time control variables, including the food price index and urban-rural area. v_t is year fixed effects, u_r is region fixed effects, δ_{rt} is interaction of year fixed effects and region fixed effects, ε is error term, and Fwt is sampling weight from the SUSENAS survey.
However, PSM cannot eliminate bias arising from unobserved variables. The researchers

aggregated data from the lowest 10% of socioeconomic households in 2017 and post-PSM household data for each subsequent year (2018, 2019, 2020, and 2021). Using a pooled cross-sectional dataset, the researchers conducted OLS estimation in equation (3), incorporating the food price index at the district level, year-fixed effects, region-fixed effects, district-fixed effects, province-fixed effects, and the interaction of province and year-fixed effects to address unobserved confounders. Including fixed effects as control variables in the estimation helps mitigate the impact of both time-variant and time-invariant effects (Kis-Katos & Sparrow, 2015; Oster, 2019).

3. RESULTS AND DISCUSSION

3.1 Pre-estimation

Through the pre-estimation propensity score matching (PSM), the researchers established treatment and control groups with comparable characteristics across the 76 covariates used. The researchers interacted the kernel weight with the SUSENAS sampling weight to estimate the population level. By aggregating data from the lowest 10% of socioeconomic households in 2017 and household data post-PSM for each year from 2018 to 2021, the estimations are restricted to beneficiaries and their counterfactuals.

The Sample Group After PSM Each Year

Table 2.	2018		2019		2020		2021	
Samples	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Unmatched	5,784	6.03%	3,985	4.12%	2,173	2.12%	889	0.85%
Matched	90,101	93.97%	92,766	95.88%	100,278	97.88%	104,221	99.15%
Total	95,885	100%	96,751	100%	102,451	100%	105,110	100%

Source: Author's Calculation

Table 3. Pooled Dataset From 2017-2021

Period	Group	Pooled Dataset	
		Frequency	Percent
2017	Control Group in Pre-Treatment Period	19,235	4.73%
Matched Samples in 2018-2021	Control Group in Post-Treatment Period	328,656	80.83%
	BPNT Beneficiaries	35,704	8.78%
	Sembako Beneficiaries	23,006	5.66%
	Total	406,601	100%

Source: Author's Calculation

Table 2 and Table 3 shows that household data from 2017 was used as the control group from the pre-treatment period, therefore no PSM was applied to the 2017 data. After performing PSM for each year in the post-treatment period (2018-2021), both matched and unmatched samples data were obtained. For the main estimation, only the matched sample data, combined with the control group data from the pre-treatment period, will be used. The distribution of pooled data by province is shown in Table 4.

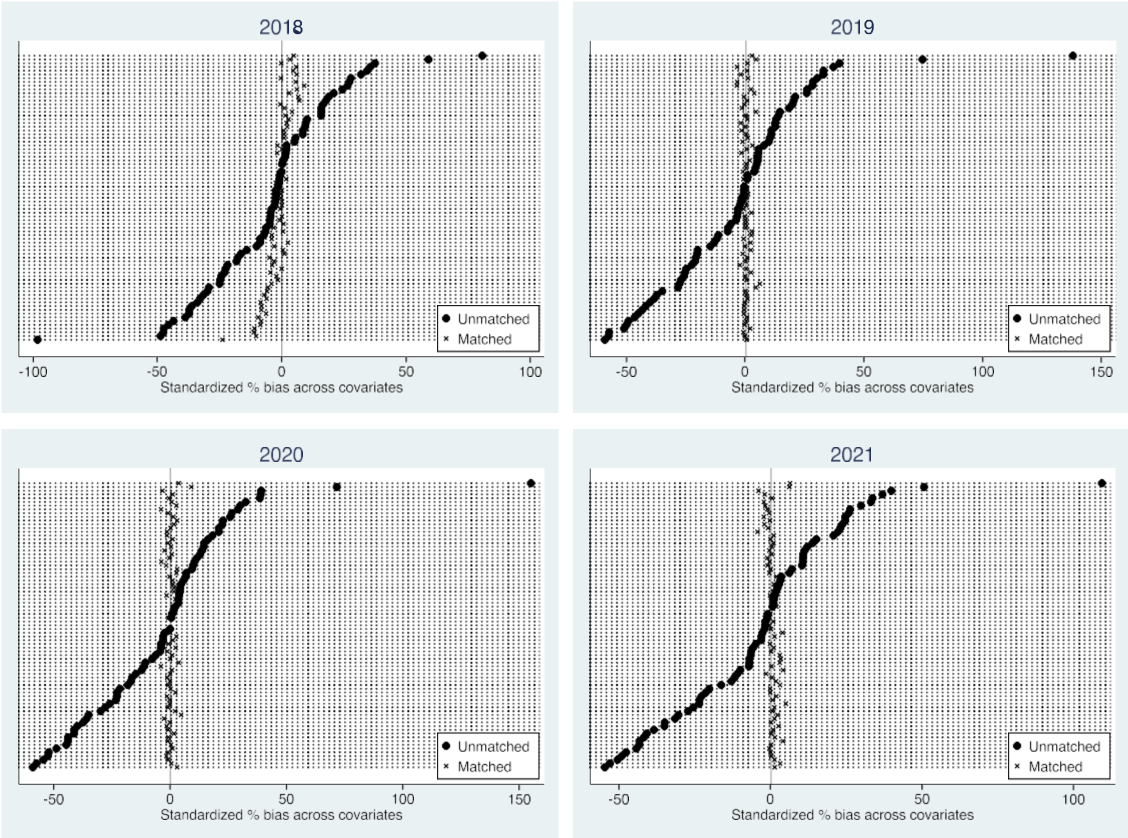

Figure 1. Covariates Balance Graph
Source: Author's Calculation

Figure 1 illustrates that, following PSM, the bias across covariates was reduced, thereby improving the accuracy of the impact estimation. As a result, differences in outcomes between the control and treatment groups were primarily attributable to treatment variables and unobserved factors. After conducting annual PSM for the post-treatment period, the researchers acquired a contemporaneous control group. This contemporaneous control group was combined with the pre-treatment control group to form the common control group. Consequently, the pooled dataset now includes three treatment groups: the control group, BPNT beneficiaries, and Sembako beneficiaries.

Table 4. Distribution of Beneficiaries Status in Java IslandSource: Author's Calculation

Province	Non-Beneficiaries		BPNT Beneficiaries		Sembako Beneficiaries		Total Pooled Data	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Banten	24,625	92.07%	1,242	4.64%	878	3.28%	26,745	100%
Yogyakarta	12,365	79.90%	1,948	12.59%	1,163	7.51%	15,476	100%
Jakarta	18,837	94.59%	690	3.46%	387	1.94%	19,914	100%
West Java	87,461	87.82%	7,637	7.67%	4,496	4.51%	99,594	100%
Central Java	96,646	82.52%	12,436	10.62%	8,040	6.86%	117,122	100%
East Java	107,957	84.51%	11,751	9.20%	8,042	6.30%	127,750	100%
Java	**347,891**	**85.56%**	**35,704**	**8.78%**	**23,006**	**5.66%**	**406,601**	**100%**

Table 4 displays the distribution of the sample used in the primary estimations. The control group, predominantly composed of non-beneficiaries, represents the largest proportion, followed by the two treatment groups: BPNT beneficiaries and Sembako Program beneficiaries. The larger proportion of BPNT beneficiaries compared to Sembako Program beneficiaries is due to the longer duration of BPNT implementation during the observation period. The Sembako Program was only introduced in 2020. Among all provinces in Java, Yogyakarta exhibits the highest proportion of beneficiaries in both the BPNT and Sembako Program, followed by Central Java and East Java.

3.2 Main Estimate Results

Using a multi-arm approach, the researchers employ a shared control group to estimate the effects of both the BPNT and Sembako Program. Since the Sembako Program is an enhancement and continuation of BPNT, the methodology aims to discern the individual impacts of each program by utilizing a unified control group. This approach allows us to compare the effects of both programs on beneficiaries, particularly in evaluating the efficacy of improvements in the food voucher program. By including control variables, the food price index, and all fixed effects, the researchers address potential upward biases in assessing reductions in Food Expenditure Share (FES) and Household Dietary Diversity Score (HDDS). Table 5 presents the estimation results obtained through this multi-arm approach. By comparing the two treatment groups with the common control group, it is evident that the Sembako Program has a more pronounced impact than BPNT on reducing beneficiaries' FES. The coefficient estimates for both programs exhibit the same level of significance. Specifically, the Sembako Program leads to a 2.50% reduction in beneficiaries' FES, whereas BPNT shows a 1.96% reduction. For the HDDS parameter, both programs show the same level of significance at $\alpha = 1\%$. The Sembako Program results in a 23.01% increase in HDDS, surpassing the 14.83% increase observed with BPNT.

Table 5. Food Voucher Impact Estimation on FES and HDDS in Java

	FES (%)	HDDS
BPNT	-1.9599***	0.1483***
	(0.2684)	(0.0338)
Sembako	-2.5036***	0.2301***
	(0.4056)	(0.0423)
Constant	64.6433	10.6351
Observation	156,401,859	156,401,859
R-squared	0.1312	0.1129
Food price index	YES	YES
Year FE	YES	YES
Urban dummies	YES	YES
District FE	YES	YES
Province FE	YES	YES
Province*Year FE	YES	YES

Standard errors are in parentheses, using double clustering at the district and treatment group level (119 districts and 2 treatment groups; non-beneficiaries and beneficiaries).
**** p<.01, ** p<.05, * p<.1.* Source: Author's Calculation

To ensure robustness, the researchers assess program impact using various cutoffs of the pre-treatment control group, representing the lowest 10%, 20%, and 30% socioeconomic levels, as depicted in Table 6. Increasing the cutoff level results in a slight decrease in the household FES reduction for BPNT from -1.96% to -1.95%, while the Sembako Program's reduction remains consistent at -2.50%. For the HDDS indicator, raising the cutoff level leads to a rise in HDDS from 14.83% to 14.98% for BPNT, and a slight decrease in the increase in HDDS from 23.01% to 22.91% for the Sembako Program. Nevertheless, minor discrepancies in the coefficient estimates for both BPNT and the Sembako Program are observed, with no variation in significance level, indicating the consistency of the estimation model.

Table 6. Robustness Check with Different Cutoffs on Pre-treatment Control Group

	FES (%)			HDDS		
	Cutoff 10%	**Cutoff 20%**	**Cutoff 30%**	**Cutoff 10%**	**Cutoff 20%**	**Cutoff 30%**
BPNT	-1.9599***	-1.9539***	-1.9453***	0.1483***	0.1487***	0.1498***
	(0.2684)	(.2675)	(.2666)	(0.0338)	(0.0338)	(0.0337)
Sembako	-2.5036***	-2.4984***	-2.4912***	.2301***	.2294***	.2291***
	(0.4056)	(0.406)	(0.4071)	(0.0423)	(0.0421)	(0.0423)
Constant	64.6433	49.3287***	59.9003***	10.6351	9.9015***	10.154***
		(2.0946)	(0.9348)	(594.4042)	(0.4595)	(0.1817)
Observation	156,401,859	164,296,754	172,,413,896	156,401,859	164,296,754	172,413,896
R-squared	0.1312	0.1307	0.1229	0.1129	0.1082	0.1044
Food price index	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Urban dummies	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Province*Year FE	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses, using double clustering at the district and treatment group level (119 districts and 2 treatment groups; non-beneficiaries and beneficiaries).
**** p<.01, ** p<.05, * p<.1.* Source: Author's Calculation

Heterogeneous Analysis by Province

Table 7 Heterogeneous Analysis for FES

	Jakarta	West Java	Central Java	Yogyakarta	East Java	Banten
BPNT	-.7862	-1.9962***	-1.8805***	-1.739**	-2.1192***	-1.8726**
	(0.7777)	(0.6239)	(0.3667)	(0.636)	(0.4506)	(0.735)
Sembako	-1.4211	-2.1936**	-2.8826***	-2.7198**	-2.6487***	-1.9714**
	(1.4343)	(1.0477)	(0.5069)	(1.1775)	(0.5394)	(0.7866)
Constant	35.3703*	69.7832***	56.1016***	52.2612***	67.7362***	59.0588***
	(18.4014)	(.9756)	(2.7156)	(6.2875)	(1.3704)	(2.0743)
Observations	13,199,095	48,080,996	37,384,850	4,218,108	44,154,011	9,364,799
R-squared	0.1269	0.1492	0.0765	0.0951	0.1019	0.1512
Food price index	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Urban	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES
Province*Year FE	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses, with double clustering at the district-treatment group level (119 districts and 2 treatment groups; non-beneficiaries and beneficiaries).
**** p<.01, ** p<.05, * p<.1.* Source: Author's Calculation

Table 7 illustrates that BPNT has a significant effect on reducing FES at $\alpha = 1\%$ in East Java, West Java, and Central Java, with Banten and Yogyakarta showing significance at $\alpha = 5\%$. However, BPNT does not exhibit a significant effect on reducing FES in Jakarta. On the other hand, the Sembako Program demonstrates a significant effect on reducing FES at α = 1% in Central Java and East Java, with Yogyakarta, West Java, and Banten showing significance at $\alpha = 5\%$. Conversely, the Sembako Program does not have a significant effect on reducing FES in Jakarta.

Table 8. Heterogenous Analysis for HDDS

	Jakarta	West Java	Central Java	Yogyakarta	East Java	Banten
BPNT	0.6956***	0.042	0.1732**	0.5207**	0.1744***	0.0372
	(0.2033)	(0.0631)	(0.0683)	(0.1675)	(0.0435)	(0.133)
Sembako	0.4481*	0.1309	0.2914***	0.7196**	0.2622***	0.0703
	(0.2406)	(0.0828)	(0.0784)	(0.2748)	(0.0571)	(0.2466)
Constant	10.4153***	10.7807***	9.8714***	9.549***	8.7083***	8.9584***
	(1.8267)	(0.1589)	(0.2978)	(0.7169)	(0.3393)	(0.5782)
Observations	13,199,095	48,080,996	37,384,850	4,218,108	44,154,011	9,364,799
R-squared	0.1135	0.1392	0.0951	0.1295	0.0764	0.145

Table 8. (continued)

	Jakarta	West Java	Central Java	Yogyakarta	East Java	Banten
Food price index	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Urban	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES
Province*Year FE	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses using double clustering at the district and treatment group level (119 districts and 2 treatment groups; non-beneficiaries and beneficiaries).
*** p<.01, ** p<.05, * p<.1.
Source: Author's Calculation

In Table 8, it is evident that BPNT has a significant effect on increasing HDDS at α = 1% in Jakarta and East Java, with Yogyakarta and Central Java showing significance at α = 5%. However, BPNT does not exhibit a significant effect on increasing HDDS in West Java and Banten. Meanwhile, the Sembako Program demonstrates a significant effect on increasing HDDS at α = 1% in Central Java and East Java, with Yogyakarta exhibiting significance at α = 5%, and Jakarta at α = 10%. Conversely, the Sembako Program does not have a significant effect on increasing HDDS in West Java and Banten.

Heterogenous Analysis by Rural-Urban

Figure 2 depicts that, initially, the mean household FES in urban areas is lower than in rural areas, suggesting that households in urban settings have better welfare than those in rural regions. These results align with research by Ardianti & Hartono (2022), which found that food insecurity is less experienced by urban households.

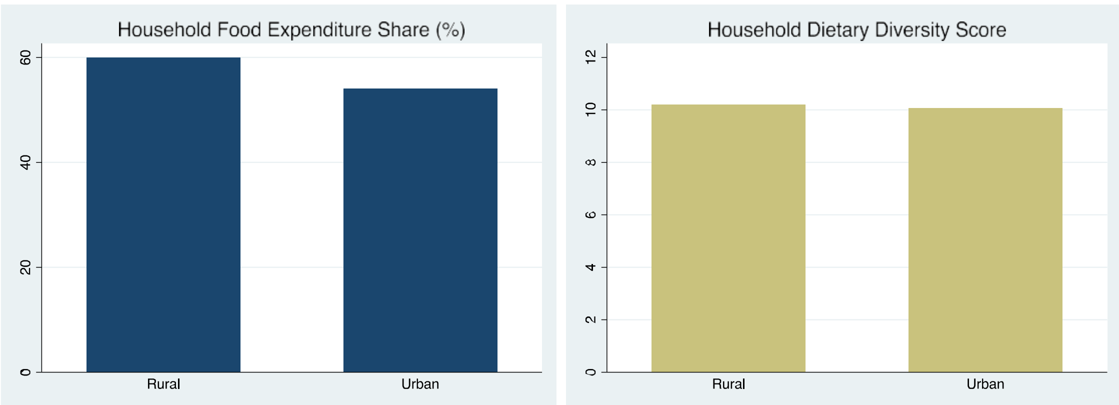

Figure 2. Household FES & HDDS in Rural-Urban Areas at Initial Level
Source: Author's Calculation

Table 9 illustrates that both the BPNT and Sembako Program significantly contribute to reducing household FES and increasing HDDS in both rural and urban areas. However, the impact of both food voucher programs on decreasing FES is more pronounced in rural areas, while the increase in HDDS is smaller in rural areas compared to urban areas. Notably, rural areas in Java exhibit substantially higher HDDS compared to urban areas at the initial level. This implies that additional income has a relatively smaller effect on groups with a higher initial level of dietary diversity and a greater effect on groups with the lowest initial level of dietary diversity (Brueckner & Lederman, 2018; McDowell et al., 1997).

Table 9. Heterogenouse Analysis of Household FES & HDDS in Rural-Urban Areas

	Rural		Urban	
	FES	**HDDS**	**FES**	**HDDS**
BPNT	-2.9433***	0.1042**	-1.1708***	0.1737***
	(0.3179)	(0.0404)	(0.4133)	(0.0538)
Sembako	-2.6106***	.1458***	-2.2882***	0.3135***
	(0.3871)	(0.0436)	(0.5818)	(0.0579)
Constant	60.8454	9.4637	67.337***	9.6062***
	(18631.577)		(1.7306)	(0.1672)
Observations	57,700,829	57,700,829	98,701,030	98,701,030
R-squared	0.1256	0.1155	0.1403	0.1362
Food price index	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Province*Year FE	YES	YES	YES	YES

Standard errors are in parentheses using double cluster at district times treatment group level (119 districts and 2 treatment groups; non-beneficiaries and beneficiaries).
**** p<.01, ** p<.05, * p<.1.* Source: Author's Calculation

3.3 Discussion

Household Food Expenditure Share (FES) and Household Dietary Diversity (HDDS) are a vital indicator of household welfare and food security, reflecting the extent to which households can satisfy their dietary needs (Yuliana et al., 2020). Engel's theory further elucidates this phenomenon by suggesting that household welfare correlates inversely with the proportion of income allocated to food expenditures. As family income increases, the percentage of income spent on food decreases. Consequently, Engel's theory posits that variations in expenditure patterns can serve as a proxy for assessing changes in population welfare levels, with modifications in expenditure composition acting as an indicator of shifts in welfare status (Wirba, 2023). HDDS as a proxy for household diet quality and indicator of access to the food component of food security (Ali et al., 2024; Mehraban & Ickowitz, 2021).

During the pre-estimation stage, we performed Propensity Score Matching (PSM) for each post-treatment year, using 76 household characteristics as covariates to estimate the likelihood of households receiving treatment. For the pre-treatment household data, we selected households from the lowest 10% of per capita expenditure in 2017 to serve as the control group for the pre-treatment period. This approach enabled us to construct pooled data from a matched sample for each post-treatment year and the pre-treatment control group, as shown in Table 3. The distribution of samples by treatment group and province from pooled dataset, is shown in Table 4. We have two types of food voucher treatments, with a common control group. These will be estimated using OLS with a multi-arm approach to compare the FES and HDDS outcomes between the two food voucher treatments.

The main estimation results for FES and HDDS in Java, shown in Table 5, indicate that the impact of a decrease in the percentage of FES and an increase in HDDS is greater for the Sembako Program beneficiaries group compared to the BPNT beneficiaries group, relative to the common control group. The results of this study fill a gap in the existing literature, as there are few studies that compare the impact of two types of food voucher flexibility. Previous studies have discussed and compared between cash, in-kind, and non-cash transfers (Banerjee et al., 2023; Doocy et al., 2020; Hidrobo et al., 2014; Michelson et al., 2012). In principle, non-cash assistance offers more flexibility than cash and in-kind assistance, thereby providing a greater welfare impact. In line with this principle, the findings of this study support previous research, showing that food voucher with higher flexibility lead to better welfare outcomes.

A more detailed analysis of the impact of food assistance at the provincial level, as shown in Table 7 and Table 8, reveals that the BPNT and Sembako Program have no effect on FES but do lead to an increase in HDDS in Jakarta Province. In contrast, in West Java and Banten provinces, the BPNT and Sembako Program reduce FES but do not significantly affect HDDS. Meanwhile, in Central Java, Yogyakarta, and East Java provinces, these programs both reduce FES and increase HDDS. The varying impact of food assistance across provinces can be influenced by several factors, including the initial conditions of beneficiaries, as well as the characteristics and availability of foodstuffs in each region (Sinaga et al., 2021).

Jakarta has the lowest poverty rate in Indonesia (BPS, 2019). Despite having the highest monthly food expenditure, the household FES remains below the national average. According to Engel's theory, this indicates that food consumption in Jakarta has reached a saturation point, where any increases in income are allocated to non-food expenses or savings. Hoynes & Schanzenbach (2009) argue that households spending less on food relative to non-food items may face constraints when utilizing food voucher. Although this may not significantly impact the household FES, as food voucher reduce out-of-pocket food expenses and shift spending towards non-food items, it results in an overall increase in both food and non-food consumption. In the other five provinces, both the BPNT and Sembako Program led to significant decreases in FES. Despite being a major food production hub with substantial food resources, studies conducted by BKP in 2017 indicate that East Java, West Java, and Banten are still classified as food-insecure regions (Prasada & Masyhuri, 2019). The Sembako Program, however, resulted in a greater reduction in FES compared to the BPNT program across all provinces. Since the Sembako Program provides higher food voucher amounts than BPNT, beneficiaries receive more additional income, leading to a more substantial decrease in FES (Athoillah et al., 2022; Sugiharti, 2020). Based on the FES reduction and its statistical significance, it can be concluded that the largest beneficiaries of both food voucher programs are in Central Java and East Java.

The BPNT and Sembako Program have no significant impact on HDDS in West Java and Banten provinces. However, both programs have a significant effect in the other four provinces. Generally, the increase in HDDS resulting from the Sembako Program was greater than that of BPNT, except in Jakarta province. In Jakarta, where agricultural land is scarce and population density is high, the demand for rice exceeds local production capacity (Alfa & Subagyo, 2018). Consequently, beneficiaries may prioritize rice purchases using food voucher. The situation in Jakarta, West Java, and Banten provinces highlights that food consumption in Indonesia remains low and less diverse, with a preference for local food and a reliance on rice as a staple (H. P. S. Rachman & Ariani, 2008). As a result, food assistance does not alter beneficiaries' preferences, nor does it encourage them to allocate their additional income toward purchasing a more diverse range of foodstuffs. Households tend to substitute commodities to buy staple foods when their income is insufficient (Yuniarti et al., 2022). Both programs show significant increases in HDDS in the provinces of Central Java, Yogyakarta and East Java. Based on the increase in HDDS and its statistical significance, it can be concluded that the largest beneficiaries of both food voucher programs are in Central Java and East Java.

Looking at the overall impact of the two programs in urban and rural areas shows that both programs have a significant impact on reducing FES and increasing HDDS in urban and rural areas. Rural areas experienced a greater decline in FES than urban areas, but a lower increase in HDDS than urban areas. Figure 2, where at baseline, rural areas have higher FES than urban areas. FES tends to be higher for households in the lower income quintiles, which are the middle- and low-income groups, with rates often exceeding 50%, indicating food insecurity (BPS, 2017; Sinaga et al., 2022). Therefore, additional income has a greater impact on reducing FES in rural areas. Figure 2 shows that the mean HDDS in urban areas is slightly lower than in rural areas at the initial level. Despite the common perception that urban areas have greater food supply, better infrastructure, and improved access to food diversity, HDDS is also influenced by sociodemographic and cultural factors (Hirvonen, 2016; Kolliesuah et al., 2023). Weerasekara et al. (2020) discovered that dietary diversity was richer in rural areas compared to urban areas, possibly due to the prevalence of agricultural households in rural settings that sell their produce in urban markets. However, the relationship between dietary diversity and market access versus 'own production' remains a subject of debate. Notably, rural areas in Indonesia are experiencing a decline in dietary diversity over time, with households consuming fewer fruits, vegetables, and legumes while increasing their consumption of dairy, eggs, and meat as their incomes rise. This trend indicates a complex interplay of nutritional gains and losses (Mehraban & Ickowitz, 2021).

Table 9 shows that BPNT results in a more significant decrease in FES than the Sembako Program in rural areas. This could be attributed to the dominance of agricultural households in rural areas, particularly in Java, which is the largest rice producer in Indonesia. In such regions, access to rice is relatively easier, even without additional income from food assistance programs. Additionally, rice consumption tends to be higher among agricultural households (BPS, 2017). By limiting BPNT benefits solely to rice and eggs, beneficiaries can allocate more vouchers towards purchasing eggs, thereby allowing them to reallocate their cash towards acquiring other food items. Research indicates that egg consumption is particularly high among animal protein sources in rural areas of Indonesia. Conversely, other animal protein sources such as beef, chicken, fish, and milk are often perceived as luxury items in rural settings (Khoiriyah et al., 2019; Suryana et al., 2021). The flexibility offered by the Sembako Program allows beneficiaries to choose other animal protein sources, which may be more costly than eggs, or to purchase additional fruits and vegetables using food voucher. However, this flexibility may still fall short of meeting all dietary requirements, compelling beneficiaries to continue using their cash to acquire additional food items. Consequently, the reduction in FES among Sembako Program beneficiaries is relatively smaller compared to BPNT beneficiaries.

4. CONCLUSIONS

This research examines the impact of food voucher programs on household Food Expenditure Share (FES) and Household Dietary Diversity Score (HDDS) within Java Island. To address potential biases arising from household characteristics influencing outcomes, a pre- estimation step was implemented. Additionally, the main estimation model incorporates both time-variant and time-invariant fixed effects to account for regional and temporal discrepancies. By employing a multi-arm treatment approach, the researchers evaluate two types of food voucher programs by comparing them to a common control group.

The findings indicate that both food voucher programs produce comparable effects on FES and HDDS, though with varying degrees of impact. Notably, the Sembako Program, which offers greater flexibility compared to BPNT, demonstrates a more pronounced effect. This suggests that the Sembako Program is more effective at reducing household FES and improving HDDS than BPNT. However, it is important to acknowledge that differing initial welfare levels can lead to varying impacts of these food voucher programs. The findings of this study provide valuable insights for the government to refine the targeting of food assistance programs, taking into account socio-demographic conditions across regions, local infrastructure, and the value of the aid distributed. This study indicates that the provinces of Central Java and East Java experience the greatest impact from the provision of food voucher, highlighting the need for the government to prioritize food assistance in these regions. Given the limitations of this study, the author suggests that future research utilize panel data or RCT methods to achieve more accurate results.

5. ACKNOWLEDGEMENT

The authors express gratitude to the supervisor, who served as an internal reviewer in the Postgraduate Program in Economics, Faculty of Economics and Business Universitas Indonesia, for their invaluable insights. Additionally, the authors extend the appreciation to the Central Bureau of Statistics for providing the necessary data for this study.

6. REFERENCES

Abdulai, A., & Kuhlgatz, C. (2011). Food Security Policy in Developing Countries. In J. L. Lusk, J. Roosen, & J. F. Shogren (Eds.), *The Oxford Handbook of the Economics of Food Consumption and Policy* (pp. 343–369). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199569441.013.0014

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., & Tobias, J. (2012). Targeting the poor: Evidence from a field experiment in Indonesia. In *American Economic Review* (Vol. 102, Issue 4, pp. 1206–1240). https://doi.org/10.1257/aer.102.4.1206

Alfa, B. N., & Subagyo. (2018). Analysis of rice supply chain mechanism with simulation approach. *IPTEK Journal of Proceedings Series*.

Ali, M. K., Berglund, L., Flacking, R., Sulaiman, M., & Osman, F. (2024). Dietary diversity and associated factors among households and children in internally displaced person camps in Southern Somalia: A cross-sectional study. *Maternal & Child Nutrition*, *20*(4). https://doi.org/10.1111/mcn.13707

Ardianti, D. M., & Hartono, D. (2022). Internet Use and Agricultural Household Food Insecurity in Indonesia. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *23*(2), 179–191. https://doi.org/10.23917/jep.v23i2.18077

Athoillah, M., Bagus Wiguna, A., & Kornitasari, Y. (2022). The Effect of Ethnicity, Demographic and Socio-economic on Households' Welfare in Indonesia. *Advances in Economics, Business and Management Research, Volume 206*.

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, *46*(3), 399–424. https://doi.org/10.1080/00273171.2011.568786

Banerjee, A., Hanna, R., Olken, B. A., Satriawan, E., & Sumarto, S. (2023). Electronic Food Vouchers: Evidence from an At-Scale Experiment in Indonesia. *American Economic Review*, *113*(2), 514–547. https://doi.org/10.1257/aer.20210461

Berg, G. D. (2011). An application of kernel-based versus one-to-one propensity score matching for a nonexperimental causal study: example from a disease management program evaluation. *Applied Economics Letters*, *18*(5), 439–447. https://doi.org/10.1080/13504851003689692

Bizikova, L., Jungcurt, S., McDougal, K., & Tyler, S. (2020). How can agricultural interventions enhance contribution to food security and SDG 2.1? *Global Food Security*, *26*, 100450. https://doi.org/10.1016/j.gfs.2020.100450

BPS. (2017). *Pengeluaran Untuk Konsumsi Penduduk Indonesia, Maret 2017*.

BPS. (2019). *Profil Kemiskinan di Indonesia Maret 2019*.

Brueckner, M., & Lederman, D. (2018). the role of initial income. *Journal of Economic Growth*, *23*(3), 341–366. https://www.jstor.org/stable/48700616

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Dewi, M. M., & Pangaribowo, E. H. (2022). The Effectiveness of Targeting Food Assistance Program in Indonesia. In • *Southeast Asian Journal of Economics* (Vol. 10, Issue 1).

Doocy, S., Busingye, M., Lyles, E., Colantouni, E., Aidam, B., Ebulu, G., & Savage, K. (2020). Cash and voucher assistance and children's nutrition status in Somalia. *Maternal and Child Nutrition*, *16*(3). https://doi.org/10.1111/mcn.12966

Elmes, M. B. (2018). Economic Inequality, Food Insecurity, and the Erosion of Equality of Capabilities in the United States. *Business & Society*, *57*(6), 1045–1074. https://doi.org/10.1177/0007650316676238

Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., & Aldridge, M. D. (2014). Methods for Constructing and Assessing Propensity Scores. *Health Services Research*, *49*(5), 1701–1720. https://doi.org/10.1111/1475-6773.12182

Hanna, R., & Olken, B. A. (2018). Universal basic incomes versus targeted transfers: Anti-poverty programs in developing countries. *Journal of Economic Perspectives*, *32*(4), 201–226. https://doi.org/10.1257/jep.32.4.201

Hermawan, I., Izzaty, Budiyanti, E., Sari, R., Sudarwati, Y., & Teja, M. (2021). The Effectiveness of Non-Cash Food Assistance Program in Yogyakarta City. *Jurnal Ekonomi & Kebijakan Publik*, *12*(2), 131–145. https://doi.org/10.22212/jekp.v12i1.2237

Hidayat, F., Hanri, M., Sastiono, P., & Moeis, J. P. (2022). *Regional Analysis of In-Kind and E-Voucher Food Assistance: The Impact of Rastra and BPNT Programs to Meet Daily Calorie Needs in Indonesia*. Universitas Indonesia.

Hidrobo, M., Hoddinott, J., Peterman, A., Margolies, A., & Moreira, V. (2014). Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador. *Journal of Development Economics*, *107*, 144–156. https://doi.org/10.1016/j.jdeveco.2013.11.009

Hirvonen, K. (2016). Rural–urban differences in children's dietary diversity in Ethiopia: A Poisson decomposition analysis. *Economics Letters*, *147*, 12–15. https://doi.org/10.1016/j.econlet.2016.08.003

Hoynes, H. W., & Schanzenbach, D. W. (2009). Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program. *American Economic Journal: Applied Economics*, *1*(4), 109–139. https://doi.org/10.1257/app

Khoiriyah, N., Anindita, R., Hanani, N., & Muhaimin, A. W. (2019). Animal Food Demand in Indonesian Rural: A Quadratic Almost Ideal Demand System Approach. *Wacana Journal of Social and Humanity Studies*, *22*(2).

Kis-Katos, K., & Sparrow, R. (2015). Poverty, labor markets and trade liberalization in Indonesia. *Journal of Development Economics*, *117*, 94–106. https://doi.org/10.1016/j.jdeveco.2015.07.005

Kolliesuah, N. P., Olum, S., & Ongeng, D. (2023). Status of household dietary diversity and associated factors among rural and urban households of Northern Uganda. *BMC Nutrition*, *9*(1), 83. https://doi.org/10.1186/s40795-023-00739-4

Kronebusch, N., & Damon, A. (2019). The impact of conditional cash transfers on nutrition outcomes: Experimental evidence from Mexico. *Economics and Human Biology*, *33*, 169–180. https://doi.org/10.1016/j.ehb.2019.01.008

McDowell, D. R., Allen-Smith, J. E., & McLean-Meyinsse, P. E. (1997). Food Expenditures and Socioeconomic Characteristics: Focus on Income Class. *American Journal of Agricultural Economics*, *79*(5), 1444–1451. https://doi.org/10.2307/1244359

Mehraban, N., & Ickowitz, A. (2021). Dietary diversity of rural Indonesian households declines over time with agricultural production diversity even as incomes rise. *Global Food Security*, *28*, 100502. https://doi.org/10.1016/j.gfs.2021.100502

Michelson, H., Lentz, E. C., Mulwa, R., Morey, M., Cramer, L., McGlinchy, M., & Barrett, C. B. (2012). Cash, food, or vouchers? An application of the Market Information and Food Insecurity Response Analysis Framework in urban and rural Kenya. *Food Security*, *4*(3), 455–469. https://doi.org/10.1007/s12571-012-0177-0

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, *37*(2), 187–204. https://doi.org/10.1080/07350015.2016.1227711

Prasada, I. M. Y., & Masyhuri. (2019). Food security in Java Island, Indonesia: Panel data of ordinary least square approach. *IOP Conference Series: Earth and Environmental Science*, *346*(1). https://doi.org/10.1088/1755-1315/346/1/012065

Rachman, B., Agustian, A., & Wahyudi, N. (2018). Efektivitas dan Perspektif Pelaksanaan Program Beras Sejahtera (Rastra) dan Bantuan Pangan Non-Tunai (BPNT). *Analisis Kebijakan Pertanian*, *16*(1), 1. https://doi.org/10.21082/akp.v16n1.2018.1-18

Rachman, H. P. S., & Ariani, M. (2008). Penganekaragaman Konsumsi Pangan Di Indonesia: Permasalahan Dan Implikasi Untuk Kebijakan Dan Program. *Analisis Kebijakan Pertanian*, *6*(2), 140–154. https://doi.org/10.21082/akp.v6n2.2008.140-154

Rahayu, R. S., Purwaningsih, Y., & Daerobi, A. (2019). Mapping Of Provincial Food Security In Indonesia Using Based Clustering Model. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *20*(1), 69–79. https://doi.org/10.23917/jep.v20i1.7096

Sadono, E. D. (2018). Impact Evaluation of Raskin Program using Matching Method: Case of IFLS 5. *JEJAK*, *11*(1), 207–223. https://doi.org/10.15294/jejak.v11i1.9192

Savy, M., Fortin, S., Kameli, Y., Renault, S., Couderc, C., Gamli, A., Amouzou, K., Perenze, M. L., & Martin-Prevel, Y. (2020). Impact of a food voucher program in alleviating household food insecurity in two cities in Senegal during a food price crisis. *Food Security*, *12*(2), 465–478. https://doi.org/10.1007/s12571-019-00996-xï

Setiawan, A. H., Agunggunanto, E. Y., & Hayati, B. (2020). Analysis of Poverty and Inequality in Java, Bali, and Lampung. *Economics Development Analysis Journal*, *9*(1), 55–64. https://doi.org/10.15294/edaj.v9i1.37865

Sinaga, R., Hutagaol, M. P., Hartoyo, S., & Nuryartono, N. (2021). Food Diversification in Java. *International Journal of Science and Society*, *3*(3), 382–389. https://doi.org/10.54783/ijsoc.v3i3.383

Sinaga, R., Hutagaol, M. P., Hartoyo, S., & Nuryartono, R. N. (2022). Analysis Food Demand of Java Households with Aids Model Estimates. *Media Ekonomi Dan Manajemen*, *37*(1), 96–108. https://doi.org/10.24856/mem.v37i1.2550

Sugiharti, D. S. S. (2020). The Economic Factors Affecting Food Security in Central Java. *The 4th International Conference on Regional Development2020*.

Suryana, E. A., Martianto, D., & Farida Baliwati, Y. (2021). Consumption, Elasticity and Demand Estimation of Animal Sources Food in Indonesia. *Agrisocionomics: Jurnal Sosial Ekonomi Pertanian*, *5*(2), 168–179. https://doi.org/10.14710/agrisocionomics.v5i2.9905

Weerasekara, P. C., Withanachchi, C. R., Ginigaddara, G. A. S., & Ploeger, A. (2020). Understanding Dietary Diversity, Dietary Practices and Changes in Food Patterns in Marginalised Societies in Sri Lanka. *Foods*, *9*(11), 1659. https://doi.org/10.3390/foods9111659

Wirba, E. L. (2023). *Identification and estimation of quadratic food Engel curves evidence from Cameroon* (523).

Yuliana, S., Teguh, M., & Imelda, I. (2020). Socioeconomic Characteristic of Household Food Security in South Sumatra. *Proceedings of the 5th Sriwijaya Economics, Accounting, and Business Conference (SEABC 2019)*, *142*. https://doi.org/10.2991/aebmr.k.200520.032

Yuniarti, D., Purwaningsih, Y., Soesilo, A., & Suryantoro, A. (2022). Food Diversification and Dynamic Food Security: Evidence from Poor Households. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *23*(1), 43–55. https://doi.org/10.23917/jep.v23i1.16302

Zaki, A., & Sulistyaningrum, E. (2021). *Evaluasi Dampak Program Sembako terhadap Konsumsi Kalori, Karbohidrat, Protein, dan Lemak serta Proporsi Pengeluaran Non Makanan pada Rumah Tangga Penerima Manfaat di Pulau Papua Tahun 2020*. Universitas Gadjah Mada.