

Non-cash food assistance and household food security: Evidence from remote Indonesia

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Abstract

Purpose — This study aims to evaluate the impact of Indonesia's Non-Cash Food Assistance Program (BPNT) on household consumption and food security in Sabu Raijua, a remote region in Indonesia with limited food access.

Methods — The Propensity Score Matching (PSM) with kernel techniques is employed to estimate the BPNT program's effects on household expenditure, caloric intake, and food insecurity using data from 536 households in Sabu Raijua, East Nusa Tenggara, Indonesia.

Findings — The results indicate that the BPNT program had a limited effect on household spending, nutrition, and food security. Beneficiary households spent slightly more on food and non-food items, showed minor improvements in nutritional intake, and were less likely to face food shortages, though concerns about food adequacy persisted.

Implications — The findings suggest that while BPNT helps alleviate food insecurity, further improvements in program implementation are needed to enhance its overall impact on household welfare.

Originality — This research provides critical insights into the effectiveness of BPNT in a remote region with unique socioeconomic challenges that have not been studied empirically, highlighting the challenges and opportunities for improving non-cash food assistance programs in similar contexts.

Keywords — BPNT, food expenditure, nutrient intake, food security

Introduction

Food insecurity remains a pressing challenge in many parts of the world, especially in regions that face environmental and socio-economic vulnerabilities (FAO, 2020). In Indonesia, a significant portion of the population struggles with poverty and malnutrition, making food assistance programs an essential component of the government's efforts to alleviate hunger and improve nutritional outcomes (Banerjee et al., 2023; Rammohan & Tohari, 2024). One such initiative is the *Bantuan Pangan Non-Tunai* (BPNT), or Non-Cash Food Assistance program, introduced by the Indonesian government in 2017. This program aims to enhance food security by providing low-income households with electronic vouchers to purchase essential food items from authorised vendors, replacing the previous *Raskin* (Rice for Poor Households) program, which distributed rice directly to beneficiaries (TNP2K, 2018).

The BPNT program is a critical component of Indonesia's social protection framework, designed to empower beneficiaries by offering flexible food choices and reducing logistical challenges associated with direct food distribution. The vouchers, worth IDR 200,000

(approximately US\$13) per month, can be redeemed for staple foods such as rice and eggs to meet the basic nutritional needs of low-income households (Government of Indonesia, 2017). This shift from in-kind distribution to electronic vouchers reflects a broader trend in social assistance programs that favours efficiency, recipient autonomy, and improved targeting to the most vulnerable populations (O'Farrell & Warokka, 2018; Timmer et al., 2017). These reforms mark a progressive step in Indonesia's fight against poverty and hunger.

While BPNT has been implemented nationwide, its effectiveness in geographically isolated regions, such as Sabu Raijua Regency in East Nusa Tenggara Province, remains uncertain. This region faces significant barriers such as poor infrastructure, high transportation costs, and limited market access, leading to food insecurity (SGP Indonesia, 2023). The National Food Agency classifies Sabu Raijua as vulnerable regarding food security, highlighting the need for targeted interventions (National Food Agency, 2021). While food assistance programs can mitigate these challenges, their success depends not only on food availability but also on vendor accessibility and distribution efficiency (Banerjee et al., 2019; Banerjee et al., 2024). Therefore, assessing the impact of BPNT in Sabu Raijua provides critical insights into the program's ability to meet its objectives in areas of food insecurity.

Food security encompasses the availability, access, and utilisation of food that meets the dietary needs and preferences of individuals (FAO, 2021). Achieving food security in regions like Sabu Raijua is particularly challenging due to high poverty levels, environmental stressors, and poor infrastructure. Even when food is available, households often struggle with the economic means to purchase it, leading to insufficient nutrition and adverse health outcomes (Skoufias et al., 2012). The BPNT program seeks to alleviate these issues by ensuring that vulnerable households have consistent access to essential food items, thereby improving overall food security and well-being. However, its impact on household food consumption and nutrition remains underexplored, particularly in remote regions where market constraints and logistical challenges may influence program effectiveness.

An ongoing debate in the literature concerns the relative effectiveness of cash versus in-kind transfers in improving food security and nutrition. The argument for providing food directly often rests on the idea that subsidising staple foods lowers food costs for vulnerable households, allowing them to spend their money on more nutritious, higher-value foods. However, evidence from programs in other countries suggests that in-kind transfers often fail to significantly improve nutrition outcomes, as they typically focus on basic grains that do not contribute to dietary diversity (Jensen & Miller, 2011; Kochar, 2005; Pingali et al., 2017; Rai et al., 2015). Conversely, some studies highlight that both food and cash have significantly different impacts on total food expenditures (Alderman et al., 2017; Banerjee et al., 2024; Cunha, 2014; Gentilini, 2016; Hidrobo et al., 2014). These findings suggest that the form of assistance provided can have significantly different impacts on food expenditure and nutritional outcomes, raising essential questions about the effectiveness of BPNT.

Although previous research has examined the general impacts of the BPNT program, there is a distinct lack of empirical evidence on its performance in challenging environments such as Sabu Raijua. This study evaluates the impact of the BPNT program on household food expenditure, caloric intake, and food security in Sabu Raijua Regency. Using Propensity Score Matching (PSM), it compares outcomes for BPNT recipients and non-recipients while controlling for household characteristics. Focusing on a region with unique socioeconomic challenges, this research aims to deepen understanding of social protection programs in areas experiencing food insecurity. The findings will provide policymakers with valuable insights and contribute to broader discussions on the use of non-cash food assistance to combat food insecurity in resource-constrained settings.

Methods

Data Source

To assess the effectiveness of the BPNT program, this research analyses data from 536 households in Sabu Raijua, East Nusa Tenggara, Indonesia. The sample includes 265 households participating in the program (treatment group) and 271 households not participating (control group). Sabu Raijua, a

geographically isolated archipelago in East Nusa Tenggara, faces severe food security challenges. Its remote location, about eight hours by sea southwest of Kupang City, combined with a drought-prone, semi-arid climate, contributes to its vulnerability (National Food Agency, 2021; SGP Indonesia, 2023). The region's food insecurity is underscored by a 33.9% stunting prevalence rate, as reported by the Indonesian Ministry of Health's Nutrition Status Study (SSGI) (Ministry of Health, 2021). These factors make Sabu Raijua an ideal case study for food security challenges.

Table 1. Research Variables

Variable	Definition
Outcome Variable	
Food expenditure	Monthly per capita expenditure on food
Non-food expenditure	Monthly per capita expenditure on non-food items
Total expenditure	Monthly per capita expenditure on food and non-food
Caloric intake	Daily caloric intake per capita
Protein intake	Daily protein intake per capita
Fat intake	Daily fat intake per capita
Carbohydrate intake	Daily carbohydrate intake per capita
Insufficiency concern	0: Worried about food sufficiency in the past year 1: Not worried
Food Intake Instability	0: Ate less due to food shortage in the past year 1: Did not eat less
Food ran out	0: Ran out of food in the past year 1: Did not run out of food
Treatment variable	
BPNT recipient	0: Non-recipient 1: Program recipient
Control variables	
Area residency	0: Urban 1: Rural
Household size	Number of household members
Sex of household head	0: Female 1: Male
Age of household head	Age of household head in years
Education level of household head	0: Not completed primary school 1: Elementary school 2: Middle school 3: High school 4: Diploma/bachelor/postgraduate
KKS ownership	0: No Kartu Keluarga Sejahtera (KKS) card 1: Has a KKS card
Employment status	0: Unemployed 1: Employed
House ownership	0: Does not own a house 1: Owns a house
Roof type	0: Other materials 1: Roof tiles or zinc material
Wall type	0: Other materials 1: Concrete or brick
Floor type	0: Other materials 1: Marble, ceramics or cement
Water-sewage distance	Distance from water access to sewage

Source: BPS (2021)

The data for this analysis is drawn from the National Socio-Economic Survey conducted in March 2021 by Statistics Indonesia (BPS). The survey included detailed information on household demographics, socio-economic characteristics, and food security indicators. Key variables include household food and non-food expenditure, caloric and nutritional intake, and food insecurity indicators such as concern about food insufficiency, reduced food consumption, and household

reports of running out of food. Covariates such as area of residence, household size, sex, age, education level, employment status, house ownership, and housing quality were also included to control for factors that might influence program participation and food security outcomes.

Analytical Strategy

Analysing at the household level enables a deeper understanding of how social assistance programs like BPNT affect food security and captures the influence of various socio-economic factors on program uptake and outcomes among vulnerable populations. This household-level approach allows for a more detailed examination of the BPNT program's effectiveness in meeting beneficiaries' food security needs in a geographically isolated, economically constrained environment.

To estimate the causal effect of BPNT on the outcome variables, this study employs PSM with kernel matching. PSM is widely used in observational studies to reduce selection bias by creating a balanced sample of treated and control units based on observable characteristics (Rosenbaum & Rubin, 1983). Since BPNT participation is not randomly assigned, differences between recipients and non-recipients could introduce bias. PSM helps approximate a randomised experiment by ensuring comparability between groups, improving the validity of causal inferences (Caliendo & Kopeinig, 2008).

While PSM does not directly enforce the parallel trends assumption, it enhances its plausibility by minimising systematic differences between groups. By balancing observable characteristics, PSM reduces the likelihood that pre-existing disparities drive differences in outcomes. This mechanism strengthens the assumption that both groups would have followed similar trends in the absence of BPNT participation, increasing the credibility of the causal estimates.

Kernel matching was chosen over other PSM methods for its efficiency and ability to use all available control observations. Unlike nearest-neighbour or calliper matching, which may exclude relevant controls, kernel matching assigns higher weights to closer matches while assigning lower weights to others. This mechanism reduces variance and improves precision, making it particularly suitable for studies with larger sample sizes, where a larger pool of control observations enhances estimation accuracy. Widely used in policy evaluations, kernel matching provides robust, balanced estimates of BPNT's impact on household food security and expenditure.

The matching procedure in this study comprises several stages. First, estimating the propensity score using a probit regression model. The propensity score is the predicted probability of receiving BPNT, where the regression takes the form:

$$\text{Probability}(bpnt = 1|X_i) = \beta_0 + \beta_i X_{ij} + \varepsilon_j \quad (1)$$

Where X_i represents the household-level covariate variables.

Second, matching observations using the kernel technique. This method utilises a weighted average of control households to match BPNT recipients with similar non-recipients, thereby reducing variance by incorporating multiple comparisons rather than relying on nearest-neighbour comparisons. The kernel weight is calculated as:

$$\omega(i, i)_{KM} = \frac{K\left(\frac{P_j - P_i}{a_n}\right)}{\sum_{k \in C} \left(\frac{P_j - P_i}{a_n}\right)} \quad (2)$$

Here, P_i and P_j represent the propensity scores of the treated and control individuals, respectively, $K(\cdot)$ is the kernel function, and a_n is the bandwidth parameter.

Third, assessing covariate balance using paired t-tests. A well-balanced dataset ensures that differences in outcomes between BPNT recipients and non-recipients are attributable to the program rather than to underlying differences in household characteristics. The t-test equation is:

$$t = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{S_T^2}{N_T} + \frac{S_C^2}{N_C}}} \quad (3)$$

Where:

- \bar{X}_T and \bar{X}_C are the means of the covariates for the treated and control groups, respectively.
- S_T^2 and S_C^2 are the variances of the covariates for the treated and control groups.

Fourth, calculating the Average Treatment Effect on the Treated (ATT) as a measurement of the intervention effect on the household outcome. It compares outcomes between BPNT recipients and their matched non-recipients, calculated as:

$$ATT = E(Y_1 - Y_0 | bpnt = 1) \quad (4)$$

Where Y_1 is the observed outcome for BPNT recipients, and Y_0 is the counterfactual outcome for non-recipients.

Finally, validating the result with Rosenbaum Sensitivity Analysis. This tests how sensitive the estimated treatment effects are to potential unobserved confounders.

$$\Gamma = \frac{P(bpnt_i=1 | X_i, U_i)}{P(bpnt_i=1 | X_i)} \quad (5)$$

The sensitivity of the results at $\Gamma=1$ (no bias) and $\Gamma=3$ (moderate bias) evaluates whether the estimated ATT remains robust under different levels of potential hidden bias. If the ATT remains significant even with $\Gamma=3$, we can conclude that the results are robust to unobserved confounders.

Results and Discussion

This section presents the findings from the PSM analysis, examining the impact of the BPNT program on household expenditure, nutritional intake, and food security in Sabu Raijua Regency. The results highlight positive trends across all three dimensions, though many observed effects are not statistically significant. This section aims to provide a detailed yet accessible interpretation of these findings, offering insight into the potential benefits of the BPNT program while acknowledging its limitations.

The impact of the BPNT program on household expenditure is positive but modest, with slight increases observed in food, non-food, and total expenditure among BPNT recipients compared to non-recipients, as shown in Table 2. Food expenditure, representing monthly per capita food spending, increased by 3.7 percentage points. The average log-transformed food expenditure for BPNT recipients was 13.11, compared to 13.08 for non-recipients, with a t-statistic of 0.64, indicating that the difference is not statistically significant. This result suggests that BPNT helps households allocate slightly more resources toward food, but the assistance provided may not be substantial enough to cause a significant shift in food spending.

Non-food expenditure, which includes spending on essential household items such as education, healthcare, and transportation, also increased by 8.5 percentage points. However, like food expenditure, this difference is not statistically significant. This result suggests that while BPNT might help households redirect some of their income toward non-food items, the assistance is too limited to substantially change non-food expenditure patterns.

Total expenditure, combining food and non-food, increased by 4.8 percentage points among BPNT recipients. Similarly, the increase is not statistically significant. This increase may suggest that BPNT helps stabilise household spending, thereby preventing consumption declines. Maintaining stable expenditure levels is a valuable outcome in regions like Sabu Raijua, where households are vulnerable to food insecurity and fluctuations in food availability.

The consistency provided by BPNT may help households maintain their standard of living, even if it does not lead to dramatic improvements in spending.

Table 2. Estimated Treatment Effects on Expenditure

Outcomes	Sample	Treated	Controls	Difference	S.E.	t-stat
ln (food expenditure)	Unmatched	13.111	13.297	-0.186	0.040	-4.630
	Matched	13.113	13.077	0.037	0.058	0.640
ln (non-food expenditure)	Unmatched	12.305	12.609	-0.304	0.071	-4.270
	Matched	12.309	12.224	0.086	0.102	0.840
ln (total expenditure)	Unmatched	13.507	13.743	-0.236	0.047	-5.000
	Matched	13.510	13.462	0.048	0.068	0.710

Source: Authors' calculation

Nutritional intake is a critical measure of the quality of household diets and directly influences health outcomes, particularly in regions where food security is a concern. The BPNT program, providing non-cash food assistance, aims to improve the nutritional status of recipient households by ensuring they have access to adequate food. This analysis examines the program's effects on caloric, protein, fat, and carbohydrate intake and reveals small positive changes, none of which are statistically significant.

Table 3. Estimated Treatment Effects on Nutritional Intake

Outcomes	Sample	Treated	Controls	Difference	S.E.	t-stat
ln(caloric)	Unmatched	7.633	7.744	-0.112	0.028	-4.020
	Matched	7.635	7.612	0.024	0.040	0.590
ln(protein)	Unmatched	4.042	4.183	-0.141	0.031	-4.510
	Matched	4.044	4.038	0.006	0.045	0.130
ln(fat)	Unmatched	3.823	3.985	-0.163	0.043	-3.780
	Matched	3.824	3.765	0.060	0.061	0.980
ln(carbohydrate)	Unmatched	5.782	5.851	-0.069	0.028	-2.500
	Matched	5.784	5.767	0.018	0.039	0.450

Source: Authors' calculation

The estimation results for nutritional intake are presented in Table 3. There was a modest 2.4 percentage-point increase in caloric intake among BPNT recipients, suggesting that the program helps households maintain or slightly increase their intake. However, this change was not large enough to be statistically significant, likely due to the limited value of assistance and other contextual factors affecting food access. Similarly, protein intake changed little, rising by only 0.6 percentage points. This suggests that while the BPNT program might help stabilise protein intake, it does not significantly increase access to protein-rich foods, which are often more expensive and less accessible in remote areas like Sabu Rajua. The limited impact on protein consumption may be due to households, despite receiving assistance, continuing to face barriers to purchasing higher-quality food items.

On the other hand, the fat intake showed a larger increase of 6.0 percentage points for BPNT recipients. Although this increase is not statistically significant, the BPNT program may contribute to a modest improvement in dietary quality, particularly in fat consumption. Fats are an important energy source and essential nutrients, and even a slight increase in fat intake could have positive implications for household nutrition. Lastly, carbohydrate intake increase of 1.8 percentage points, reflecting the program's minor effect on carbohydrate consumption. This is likely because staple foods like rice and cassava already form a substantial part of the diet in the region, and BPNT assistance may not significantly alter these existing consumption patterns.

Food security is a central objective of the BPNT program, as it aims to ensure that households have consistent access to sufficient and nutritious food. The analysis of food security indicators provides insight into how BPNT affects households' experiences of food scarcity and insecurity. The three indicators analysed—insufficiency concern, food intake instability, and food running out—offer a comprehensive view of food security among recipient households.

Table 4. Estimated Treatment Effects on Food Security

Outcome	Sample	Treated	Controls	Difference	S.E.	t-stat
Insufficiency concern	Unmatched	0.691	0.819	-0.129	0.037	-3.500
	Matched	0.695	0.749	-0.054	0.048	-1.130
Food intake instability	Unmatched	0.936	0.945	-0.009	0.021	-0.430
	Matched	0.935	0.901	0.034	0.027	1.250
Food ran out	Unmatched	0.981	0.974	0.007	0.013	0.540
	Matched	0.981	0.950	0.031	0.018	1.670

Source: Authors' calculation

The estimation results for food security are presented in Table 4. For the insufficiency concern indicator, which measures whether households were worried about having enough food

in the past year, BPNT recipients reported slightly more concern than non-recipients. Among BPNT recipients, 69.5% reported not being concerned about food insufficiency, compared to 74.9% of non-recipients, resulting in a difference of -5.4 percentage points. Although this result is not statistically significant, it suggests that BPNT households may still face significant food security concerns despite receiving assistance. This condition could be due to broader economic factors in Sabu Raijua, such as seasonal food shortages, high prices, and limited market access, which may contribute to ongoing concerns about food sufficiency.

In contrast, the food intake instability indicator, which measures whether households had to eat less due to food shortages, showed a more favourable result. Among BPNT recipients, 93.5% reported not eating less due to food shortages, compared with 90.1% of non-recipients, a difference of 3.4 percentage points. While this result is not statistically significant, BPNT may help some households avoid reducing their food consumption during times of scarcity. This is an important finding, as reducing food intake can seriously affect household health and nutrition, particularly in vulnerable populations. Although modest, the result indicates that BPNT may play a protective role in maintaining food intake during economic or environmental stress periods.

The food ran out indicator, which measures whether households experienced running out of food in the past year, showed the most desirable outcome. Among BPNT recipients, 98.1% reported they were not running out of food, compared with 95.0% of non-recipients, a difference of 3.1 percentage points. This result approaches statistical significance at the 10% level, suggesting that BPNT may provide a crucial buffer against extreme food insecurity. Running out of food is one of the most severe forms of food insecurity, and the fact that BPNT recipients were less likely to experience this outcome indicates that the program is making a tangible difference in the lives of vulnerable households.

To ensure the reliability of the findings, this study conducted paired t-tests before and after matching, and the Rosenbaum bounds test to assess the sensitivity of our results to unobserved variables. These methods were chosen to mitigate potential biases in the analysis and strengthen the validity of the causal inferences regarding the BPNT program's impact.

Table 5. The Balancing Check

Variable	Sample	Mean		Bias (%)	Bias reduction (%)	t-test	
		Treated	Control			t	p> t
Area residency	Unmatched	0.030	0.114	-32.90	97.20	-3.80	0.000
	Matched	0.031	0.033	-0.90		-0.16	0.876
Household size	Unmatched	4.849	3.712	54.10	90.70	6.27	0.000
	Matched	4.786	4.680	5.10		0.57	0.567
Sex of household head	Unmatched	0.819	0.804	3.70	82.90	0.43	0.670
	Matched	0.817	0.819	-0.60		-0.07	0.942
Age of household head	Unmatched	50.687	47.554	20.20	52.10	2.34	0.020
	Matched	50.538	52.040	-9.70		-1.16	0.245
Education of the household head	Unmatched	0.834	1.384	-48.60	87.80	-5.61	0.000
	Matched	0.836	0.769	5.90		0.85	0.398
KKS ownership	Unmatched	0.525	0.140	89.20	99.10	10.34	0.000
	Matched	0.519	0.523	-0.80		-0.08	0.934
Employment status	Unmatched	0.940	0.886	19.20	96.60	2.22	0.027
	Matched	0.939	0.941	-0.70		-0.09	0.929
House ownership	Unmatched	0.947	0.900	17.70	63.80	2.04	0.042
	Matched	0.946	0.964	-6.40		-0.93	0.351
Roof type	Unmatched	0.528	0.598	-14.00	92.50	-1.62	0.105
	Matched	0.527	0.532	-1.00		-0.12	0.905
Wall type	Unmatched	0.426	0.469	-8.50	63.10	-0.98	0.327
	Matched	0.424	0.408	3.10		0.36	0.718
Floor type	Unmatched	0.460	0.502	-8.30	58.10	-0.96	0.338
	Matched	0.458	0.475	-3.50		-0.40	0.691
Water-sewage distance	Unmatched	0.902	0.804	27.70	59.10	3.21	0.001
	Matched	0.9008	0.8610	11.30		1.41	0.160

Source: Authors' calculation

First, this study performed paired t-tests to evaluate the balance of covariates between the treatment and control groups before and after matching, as shown in Table 5. Before matching, there were significant differences between the groups in key covariates, such as household size, employment status, and education level, that could bias estimates of the program's impact. However, after matching, the paired t-test results showed no statistically significant differences between the two groups across these observable characteristics. This result demonstrates that PSM successfully reduced bias introduced by differences in observed covariates, yielding a more comparable sample for analysis. By improving the balance between treated and untreated households, the method enhances the reliability of our estimates by focusing on households with similar observed characteristics, thereby reducing selection bias.

Furthermore, this study applied the Rosenbaum bounds test to evaluate the sensitivity of our results to potential hidden biases. For key outcome variables such as food expenditure per capita, non-food expenditure per capita, total expenditure per capita, caloric intake, protein intake, fat intake, and carbohydrate intake, the Rosenbaum bounds analysis showed that unobserved confounders did not significantly affect the estimated treatment effects. Specifically, the bounds analysis indicated that our findings were robust to hidden biases within a reasonable range ($\Gamma = 1$ to $\Gamma = 3$), as there were no significant deviations in the results for most outcomes, including household food security measures such as insufficiency concern, instances of eating less due to food shortages, and food running out. These findings suggest that the observed treatment effects of the BPNT program are stable and not easily confounded by unobserved variables.

Table 6. The Rosenbaum Bounds Results

	Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
ln(food expenditure)							
	1	0	0	13.19	13.19	13.15	13.23
	3	0	0	12.97	13.42	12.93	13.47
ln(non-food expenditure)							
	1	0	0	12.48	12.48	12.41	12.56
	3	0	0	12.05	12.87	11.97	12.94
ln(total expenditure)							
	1	0	0	13.62	13.62	13.57	13.67
	3	0	0	13.35	13.89	13.30	13.95
ln(caloric)							
	1	0	0	7.68	7.68	7.65	7.71
	3	0	0	7.52	7.85	7.49	7.88
ln(protein)							
	1	0	0	4.10	4.10	4.07	4.13
	3	0	0	3.93	4.28	3.89	4.32
ln(fat)							
	1	0	0	3.90	3.90	3.85	3.94
	3	0	0	3.66	4.14	3.61	4.20
ln(carbohydrate)							
	1	0	0	5.82	5.82	5.79	5.84
	3	0	0	5.66	5.97	5.63	6.01
Insufficiency concern							
	1	0	0	1.00	1.00	1.00	1.00
	3	0	0	0.50	1.00	0.50	1.00
Food intake instability							
	1	0	0	1.00	1.00	1.00	1.00
	3	0	0	1.00	1.00	1.00	1.00
Food ran out							
	1	0	0	1.00	1.00	1.00	1.00
	3	0	0	1.00	1.00	1.00	1.00

Source: Authors' calculation

*gamma: log odds of differential assignment due to unobserved factors

sig+ : upper bound significance level

sig- : lower bound significance level

- t-hat+ : upper bound Hodges-Lehmann point estimate
- t-hat- : lower bound Hodges-Lehmann point estimate
- CI+ : upper bound confidence interval ($\alpha = 0.95$)
- CI- : lower bound confidence interval ($\alpha = 0.95$)

The combination of PSM and the Rosenbaum bounds test provides a comprehensive approach to reducing bias and validating the results, as presented in Table 6. PSM addressed observable bias by matching similar households, thereby controlling for confounding variables that could distort the treatment effects. Meanwhile, the Rosenbaum bounds test extended the robustness check by examining the influence of unobserved bias. Together, these methods significantly reduce the risk of bias in the estimates, reinforcing the causal interpretation of the BPNT program's impact on household consumption and food security outcomes.

The BPNT program in Indonesia has demonstrated the potential to positively impact household outcomes, particularly in stabilising food expenditure, enhancing nutritional intake, and improving food security. These outcomes align with findings from conditional cash transfer programs in other countries, which have similarly contributed to poverty alleviation and improved household consumption patterns (Banerjee et al., 2023; Habimana et al., 2021; Nazareno & de Castro Galvao, 2023; Parker & Todd, 2017; Torres et al., 2025). The BNPT program provides non-cash food assistance to low-income households through electronic vouchers redeemable for essential food items. While this initiative has led to modest increases in both food and non-food expenditures and improvements in food security indicators, the observed effects in this study were not statistically significant. Several factors may explain both the program's positive contributions and the lack of significant results, with important implications for the future design and implementation of food assistance programs.

One key factor contributing to the BPNT program's positive effects on household welfare is its ability to provide direct financial relief. By offering food vouchers, the program effectively increases the purchasing power of low-income households, allowing them to access essential staples that might otherwise be unaffordable due to economic constraints (Egger et al., 2022; Filmer et al., 2023; Skoufias et al., 2013). The small positive changes in both food expenditure and total expenditure observed in this study suggest that the program enables households to maintain consistent consumption levels even during financial difficulties.

Moreover, the BPNT program plays a crucial role in stabilising food security outcomes, particularly in preventing households from running out of food. This aligns with findings from Hidrobo et al. (2014), Gadenne et al. (2024) and McIntosh and Zeitlin (2024), which highlight the effectiveness of food assistance programs in reducing extreme food insecurity. BPNT appears to serve as a safety net against the most severe forms of food deprivation, ensuring that vulnerable households do not experience shortages. This function is especially critical in remote regions such as Sabu Raijua, where geographic and market constraints limit access to food.

Despite these positive trends, the lack of statistical significance in most results may be due to several external factors, particularly food prices and market access, which directly affect the effectiveness of non-cash food assistance programs like BPNT. In remote regions like Sabu Raijua, where food supply chains are weak and transportation costs are high, food prices tend to be significantly elevated (Barrett et al., 2022; Nava et al., 2023). This reduces the purchasing power of BPNT vouchers, making it difficult for recipient households to obtain sufficient quantities and varieties of food items. Previous studies have shown that when market inefficiencies persist, well-intended aid interventions may fail to produce meaningful improvements in household welfare (Cunha et al., 2019; Hirvonen & Hoddinott, 2021). The price elasticity of demand for food in such areas means that a relatively small price increase can substantially erode the value of assistance, leaving households still vulnerable to food insecurity.

Limited market access further weakens the effectiveness of BPNT in Sabu Raijua. Many BPNT households rely on local vendors, but poor infrastructure, weak market integration, and supply shortages mean that even with vouchers, food choices remain limited (Wang et al., 2022). The success of food assistance programs depends not only on household purchasing power but also on the availability and affordability of essential food items (Hidrobo et al., 2014; McIntosh &

Zeitlin, 2024). When vendors face logistical difficulties replenishing stock, food supplies may be irregular, further reducing the intended benefits of BPNT. This issue is exacerbated when transport costs are passed on to consumers, effectively increasing the cost of basic food staples beyond what the voucher system can accommodate.

The findings of this study have significant implications for social policy in Indonesia and other developing nations implementing non-cash food assistance programs. While the BPNT program shows potential to stabilise household food security, its modest, statistically insignificant impact suggests that further policy improvements are necessary to maximise its effectiveness. To achieve this, policymakers should consider adjusting the value of food vouchers, improving market access, and considering complementary interventions. Strengthening these aspects would enable BPNT to better support households in achieving sustainable food security and overall well-being.

Firstly, the limited impact of BPNT on food expenditure and nutritional intake suggests that the value of food vouchers may be insufficient to achieve meaningful improvements in dietary diversity and overall food security. To ensure beneficiaries can access a more nutritionally diverse food basket, policymakers should adjust voucher values to account for inflation and regional price variations. Aligning food assistance with local economic conditions has proven effective in other contexts, as evidenced by global best practices in which targeted food programs have been adapted to specific economic realities. Studies have shown that food assistance programs are more effective when they account for local market fluctuations and purchasing power, ensuring that beneficiaries receive adequate support to meet their nutritional needs (Cunha et al., 2019; Hirvonen & Hoddinott, 2021).

Secondly, geographic disparities in BPNT's effectiveness further highlight the need for localised policy adaptations. In isolated areas, exemplified by Sabu Raijua, elevated food transport costs and restricted market access substantially undermine household food security. To address this issue, policymakers should explore complementary interventions, such as transportation subsidies for food vendors, investments in local food production, and improved distribution logistics. These measures would strengthen market access and enhance the efficiency of food assistance delivery. A relevant example is Ethiopia's Productive Safety Net Programme (PSNP), which successfully supplemented cash transfers with local infrastructure investments and packages of agricultural support to improve food accessibility in hard-to-reach areas (Gilligan et al., 2009; Mustafa et al., 2023). This demonstrates the potential of such integrated approaches to improve outcomes for vulnerable populations.

Furthermore, the findings indicate that while BPNT recipients experience slight improvements in food security, concerns about food insufficiency persist. This suggests that non-cash food assistance alone may not be sufficient to address broader issues of poverty and economic vulnerability in an isolated region. Therefore, achieving sustainable food security requires a wider policy approach. Food security policies must be embedded within comprehensive economic and social frameworks that prioritise adequate income for all and control the costs of essential goods and services (Penne & Goedemé, 2021). Integrating BPNT with other social protection measures, such as employment programs, microfinance initiatives, and nutrition education, could amplify its impact. This integrated approach would allow BPNT to transcend short-term food assistance and contribute to long-term poverty reduction and increased household resilience.

Incorporating these targeted improvements would enhance BPNT's ability to combat food insecurity and support long-term well-being for vulnerable populations. By refining its design and implementation, Indonesia can create a more effective and resilient social protection system that better serves the needs of its people. A more responsive and adaptive BPNT program would not only strengthen household food security but also provide a model for other developing nations seeking to optimise their food assistance programs.

Conclusion

This study assessed the impact of Indonesia's Non-Cash Food Assistance Program (BPNT) on household consumption and food security in Sabu Raijua, a remote region with significant economic and logistical challenges. The findings suggest that while the BPNT program has a

positive effect on household food and non-food expenditure, nutritional intake, and food security, most of the observed changes are modest and not statistically significant. The program showed potential to stabilise household consumption, particularly by preventing food shortages, but its overall impact remains limited.

Beyond these empirical findings, this study contributes to both scholarly and policy discussions on non-cash food assistance and household food security. In the academic domain, this research adds empirical insights into non-cash food assistance in an emerging economy, particularly in contexts where both economic constraints and supply-side limitations drive food insecurity. By employing PSM to control selection bias, this study also contributes methodological insights for future evaluations of social assistance programs in developing economies. From a policy perspective, the results underscore the need to refine the design and implementation of programs like BPNT, especially in regions with limited market access and high food prices. Insights from this study can inform policy adjustments to improve effectiveness.

The findings of this study underscore the need for strategic policy enhancements to improve the effectiveness of the BPNT program in ensuring food security for vulnerable households. Given the modest and statistically insignificant impact observed, policymakers should consider adjusting food voucher values to reflect inflation and regional price variations, ensuring that beneficiaries can afford a nutritionally adequate diet. Additionally, addressing geographic disparities through targeted interventions, such as transportation subsidies, investments in local food production, and improved distribution networks, would enhance access to affordable food in remote areas. Beyond food assistance, integrating BPNT with broader social protection initiatives—including employment programs, microfinance, and nutrition education—could provide a more comprehensive approach to poverty reduction. These recommendations would strengthen the program's ability to support sustainable food security and overall well-being.

However, this study has some limitations. The cross-sectional nature of the data limits the ability to capture the long-term effects of the BPNT program, as the analysis provides only a snapshot of its impact at a specific point in time. Future studies could address this limitation by employing longitudinal data to examine the program's effects over time and conducting comparative analyses to account for geographic and economic variations. Additionally, while helpful in addressing selection bias, the use of PSM in this analysis has limitations. PSM assumes that all relevant confounding variables are observed and accounted for, which may not be held in practice. Future studies could use alternative methods, such as Randomised Controlled Trials or Instrumental Variables, to address the issue of unobserved confounders.

In brief, the BPNT program provides a valuable framework for supporting food security in vulnerable regions. However, its current limitations indicate a need for strategic improvements. By addressing these challenges and enhancing program implementation, there is potential for significantly improving the lives of households in this underprivileged region. Continued research will be essential to evaluate its long-term effectiveness further and ensure that aid reaches those who need it most.

Author contributions

Rizki Tri Anggara: Conceptualisation, Writing—original draft, Formal analysis, Methodology, Writing—review.

Elsya Gumayanti Alfahma: Writing—review & editing, Formal analysis, Visualisation, Validation.

Use of AI tools declaration

The authors used AI tools (ChatGPT and DeepSeek) for language editing and grammar review of this manuscript. The authors are fully responsible for the content of this publication.

Conflict of interest

The authors declare no conflicts of interest.

References

- Alderman, H., Alderman, H., Gentilini, U., & Yemtsov, R. (2017). *The 1.5 Billion People Question: Food, Vouchers, or Cash Transfers?* The World Bank.
- Banerjee, A., Hanna, R., Kyle, J., Olken, B. A., & Sumarto, S. (2019). Private outsourcing and competition: Subsidized food distribution in Indonesia. *Journal of Political Economy*, 127(1), 101–137. <https://doi.org/10.1086/700734>
- Banerjee, A., Hanna, R., Olken, B. A., & Diana Sverdlin, L. (2024). Social Protection in the Developing World. In. Cambridge: National Bureau of Economic Research, Inc.
- 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>
- Barrett, C. B., Reardon, T., Swinnen, J., & Zilberman, D. (2022). Agri-food value chain revolutions in low- and middle-income countries. *Journal of Economic Literature*, 60(4), 1316–1377. <https://doi.org/10.1257/jel.20201539>
- 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>
- Cunha, J. M. (2014). Testing paternalism: Cash versus in-kind transfers. *American Economic Journal: Applied Economics*, 6(2), 195–230. <https://doi.org/10.1257/app.6.2.195>
- Cunha, J. M., De Giorgi, G., & Jayachandran, S. (2019). The price effects of cash versus in-kind transfers. *The Review of Economic Studies*, 86(1), 240–281. <https://doi.org/10.1093/restud/rdy018>
- Egger, D., Haushofer, J., Miguel, E., Niehaus, P., & Walker, M. (2022). General equilibrium effects of cash transfers: Experimental evidence from Kenya. *Econometrica*, 90(6), 2603–2643. <https://doi.org/10.3982/ECTA17945>
- FAO. (2020). *The state of food security and nutrition in the world 2020: transforming food systems for affordable healthy diets*. <https://openknowledge.fao.org/handle/20.500.14283/ca9692en>
- FAO. (2021). *The state of food security and nutrition in the world 2021: Making Agrifood Systems More Resilient To Shocks And Stresses*. <https://openknowledge.fao.org/server/api/core/bitstreams/1e61f82a-618c-467a-a37f-545580094a1d/content>
- Filmer, D., Friedman, J., Kandpal, E., & Onishi, J. (2023). Cash transfers, food prices, and nutrition impacts on ineligible children. *The Review of Economics and Statistics*, 105(2), 327–343. https://doi.org/10.1162/rest_a_01061
- Gadenne, L., Norris, S., Singhal, M., & Sukhtankar, S. (2024). In-kind transfers as insurance. *American Economic Review*, 114(9), 2861–2897. <https://doi.org/10.1257/aer.20220822>
- Gentilini, U. (2016). Revisiting the “cash versus food” debate: New evidence for an old puzzle? *The World Bank Research Observer*, 31(1), 135–167. <https://doi.org/10.1093/wbro/lkv012>
- Gilligan, D. O., Hoddinott, J., & Taffesse, A. S. (2009). The impact of Ethiopia’s productive safety net programme and its linkages. *Journal of Development Studies*, 45(10), 1684–1706. <https://doi.org/10.1080/00220380902935907>
- Government of Indonesia. (2017). *Presidential Regulation Number 63 of 2017 on the Distribution of Non-Cash Social Assistance*. <https://peraturan.bpk.go.id/Details/73010/perpres-no-63-tahun-2017>

- Habimana, D., Haughton, J., Nkurunziza, J., & Haughton, D. M.-A. (2021). Measuring the impact of unconditional cash transfers on consumption and poverty in Rwanda. *World Development Perspectives*, 23, 100341. <https://doi.org/10.1016/j.wdp.2021.100341>
- 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., & Hoddinott, J. (2021). Beneficiary views on cash and in-kind payments: Evidence from Ethiopia's productive safety net programme. *The World Bank Economic Review*, 35(2), 398–413. <https://doi.org/10.1093/wber/lhaa002>
- Jensen, R. T., & Miller, N. H. (2011). Do consumer price subsidies really improve nutrition? *Review of Economics and Statistics*, 93(4), 1205–1223. https://doi.org/10.1162/REST_a_00118
- Kochar, A. (2005). Can targeted food programs improve nutrition? An empirical analysis of India's public distribution system. *Economic Development and Cultural Change*, 54(1), 203–235. <https://doi.org/10.1086/431260>
- McIntosh, C., & Zeitlin, A. (2024). Cash versus kind: Benchmarking a child nutrition program against unconditional cash transfers in Rwanda. *The Economic Journal*, 134(664), 3360–3389. <https://doi.org/10.1093/ej/ueae050>
- Ministry of Health. (2021). *Indonesian Nutritional Status Study (SSGI) Year 2021*. <https://www.badankebijakan.kemkes.go.id/buku-saku-hasil-studi-status-gizi-indonesia-ssgi-tahun-2021/>
- Mustafa, M. N., Asfaw, F. F., Endris, A. E., & Bojago, E. (2023). Evaluating the impact of productive safety net program on rural household food security achievement: Endogenous switching regression modeling approach. *Journal of Agriculture and Food Research*, 14, 100674. <https://doi.org/10.1016/j.jafr.2023.100674>
- National Food Agency. (2021). *Food security and vulnerability atlas 2021*. National Food Agency. Retrieved 26 September 2024 from <https://fsva.badanpangan.go.id/>
- Nava, N. J., Ridley, W., & Dall'erba, S. (2023). A model of the U.S. food system: What are the determinants of the state vulnerabilities to production shocks and supply chain disruptions? *Agricultural Economics*, 54(1), 95-109. <https://doi.org/10.1111/agec.12750>
- Nazareno, L., & De Castro Galvao, J. (2023). The impact of conditional cash transfers on poverty, inequality, and employment during Covid-19: A case study from Brazil. *Population Research and Policy Review*, 42(2), 22. <https://doi.org/10.1007/s11113-023-09749-3>
- O'Farrell, S., & Warokka, T. (2018). *Indonesia's non-cash social assistance reform: An analysis of TNP2K's contribution*. <https://www.dfat.gov.au/sites/default/files/indonesias-non-cash-social-assistance-reform-an-analysis-of-tnp2ks-contribution.pdf>
- Parker, S. W., & Todd, P. E. (2017). Conditional Cash Transfers: The Case of Progres/Oportunidades. *Journal of Economic Literature*, 55(3), 866–915. <https://doi.org/10.1257/jel.20151233>
- Penne, T., & Goedemé, T. (2021). Can low-income households afford a healthy diet? Insufficient income as a driver of food insecurity in Europe. *Food Policy*, 99, 101978. <https://doi.org/10.1016/j.foodpol.2020.101978>
- Pingali, P., Mitra, B., & Rahman, A. (2017). The bumpy road from food to nutrition security – Slow evolution of India's food policy. *Global Food Security*, 15, 77-84. <https://doi.org/10.1016/j.gfs.2017.05.002>

- Rai, R. K., Kumar, S., Sekher, M., Pritchard, B., & Rammohan, A. (2015). A life-cycle approach to food and nutrition security in India. *Public health nutrition*, 18(5), 944-949. <https://doi.org/10.1017/S1368980014001037>
- Rammohan, A., & Tohari, A. (2024). Food vouchers and dietary diversity: evidence from social protection reform in Indonesia. *Food security*, 16(1), 161-184. <https://doi.org/10.1007/s12571-023-01413-0>
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55. <https://doi.org/10.1093/biomet/70.1.41>
- SGP Indonesia. (2023). *Sabu Raijua Islands Baseline Survey and Strategic Plan for GEF SGP Program 2022-2026*. <https://sgp-indonesia.org/wp-content/uploads/2024/01/Laporan-Sabu-Final-Layouted-eng.pdf>
- Skoufias, E., Tiwari, S., & Zaman, H. (2012). Crises, food prices, and the income elasticity of micronutrients: Estimates from Indonesia. *The World Bank Economic Review*, 26(3), 415–442. <https://doi.org/10.1093/wber/lhr054>
- Skoufias, E., Unar, M., & Gonzalez De Cossio, T. (2013). The poverty impacts of cash and in-kind transfers: Experimental evidence from rural Mexico. *Journal of Development Effectiveness*, 5(4), 401–429. <https://doi.org/10.1080/19439342.2013.843578>
- Timmer, C., Hastuti, H., & Sumarto, S. (2017). *Evolution and Implementation of the Rastra Program in Indonesia*. <https://EconPapers.repec.org/RePEc:pra:mprapa:81018>
- TNP2K. (2018). *The future of the social protection system in Indonesia: social protection for all*. <https://tnp2k.go.id/downloads/the-future-of-the-social-protection-system-in-indonesia>
- Torres, T. d. F., Marques, M. L. V., Cezar, C. A. P., Uhr, D. de A. P., Uhr, J. G. Z., & Carraro, A. (2025). A study on the effect of the Brazilian conditional cash transfer program on child nutrition. *International Journal of Social Economics*. <https://doi.org/10.1108/IJSE-03-2023-0216>
- Wang, J., Ding, X., Gao, H., & Fan, S. (2022). Reshaping food policy and governance to incentivize and empower disadvantaged groups for improving nutrition. *Nutrients*, 14(3), 648. <https://doi.org/10.3390/nu14030648>