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Wahyuni Andriana Sofa
Politeknik Statistika STIS, anasofa@stis.ac.id

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From Rastra to BPNT: An Empirical Quantitative Evaluation of Food Assistance Reform in Indonesia

Wahyuni Andriana Sofa[a,*]

[a] *Politeknik Statistika STIS*

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Abstract

Since 2017, Indonesia has shifted from its Rastra program to BPNT, an e-voucher food-based initiative, due to issues with targeting and effectiveness in social assistance. This paper examines the impact of this transition on poverty alleviation and food security, using SUSENAS 2018 and propensity score matching. Findings indicate BPNT is less effective than Rastra in reducing households' poverty risk and has led to decreased food access and nutrition. Impact variations are noted, which are found to be worse in households with less-educated heads, located in Java Island, and rural areas.

Keywords: BPNT, evaluation, propensity score, Rastra, SUSENAS

JEL classifications: I38; O12; O22

1. Introduction

The failure to stabilize rice prices associated with the 1997 Asian financial crisis has led to food insecurity in Indonesia. In response, the government has initiated a program named Subsidized Prosperous Rice or Rastra (formerly Rice for the Poor or Raskin) which supplies rice for the poor at a heavily subsidized price. Among all instruments of social protection, Rastra has been recognized as the most potential and well-funded scheme, covering nearly half of the Indonesian population as measured in 2016 (OECD 2019). Despite this remarkable achievement, Rastra faces significant challenges related to targeting, diluted benefits, and rice shortage (World Bank 2017). In addition, the increasing amount of subsidy poses a heavier burden on the government budget year after year. Therefore, since 2017, the government has advocated for revisions of Rastra by introducing the Non-Cash Food Assistance (BPNT) initiative, aiming to address the delivery inefficiencies of its predecessor. While the former remains in operation, BPNT has been gradually introduced in several parts of the country, with complete implementation targeted by 2019. This study seeks to assess whether this reform can effectively achieve its desired objectives by comparing the impacts of Rastra and BPNT on poverty alleviation and food security.

It is common for every social transfer intervention to encounter certain design issues such as determining the beneficiaries of the program as well as deciding the amount, duration, and the form of assistance to optimize potential benefits considering various options available. In particular, cash versus voucher transfers in social assistance has become a long-standing discussion in economics. Numerous studies have been conducted to assess the effectiveness and offer recommendations concerning all types of assistance programs, which somehow suggest mixed results. A recent study by Hidrobo et al. (2014), compares cash, in-kind, and voucher transfers using a randomized experiment in North Ecuador to evaluate their impacts on food consump-

*Corresponding Address: Department of Statistics, Politeknik Statistika STIS Jl. Otto Iskandardinata 64C, Jakarta, Indonesia. Email: anasofa@stis.ac.id.

tion. The findings indicate that food transfer leads to increased calorie intake, while voucher transfer proves beneficial to achieve food diversification. Although it is claimed to reveal the real impacts, it may not always be easy to replicate this type of assessment due to the time and budget constraint.

A similar recent study contributing to the debate was conducted by Brugh et al. (2018) in Malawi using a cluster-randomized controlled trial panel data to evaluate the impact of an unconditional cash transfer on nutrition and food security. Their finding indicates that cash transfer is more likely to improve household diet quality. Unfortunately, they do not incorporate other types of assistance into comparison and the estimated outcomes suffer from measurement errors. Applying a similar approach, Aker (2013) discovers no evidence of differential food security improvement resulting from different types of transfer. Nonetheless, most of these existing studies rely on economic theory predicting that an individual will likely benefit more from cash than voucher or in-kind transfers.

The attempt to reduce household vulnerability to extreme poverty and strengthen food security through social protection strategies has been increasingly applied in numerous developing countries, including Indonesia. In this country, the Rastra program is a part of social protection strategies that has recently undergone significant reform. Rastra continues to be implemented in the majority of provinces in Indonesia except in the eastern parts where supporting facilities are limited. Nevertheless, the government has recently started enacting its successor with a growing number of beneficiaries. An evaluation is thus needed to test whether the economic prediction on the benefit of transforming cash to voucher applies in this situation. Unfortunately, empirical evidence to support this theory in Indonesia is scarce. While there exists a strand of literature which evaluates Rastra, such as those by Kustianingrum & Terawaki (2017), Sumarto, Suryahadi & Widyanti (2005), and Pangaribowo (2012), no assessment is available following the transition to the non-cash program. It is because the non-cash initiative has only recently been developed in Indonesia.

To test the theory, this study examines the effects of the food reform on improving social welfare and food security. The main purpose is to obtain a thorough understanding of the differences between the two initiatives and propose recommendations for the decision-making process regarding the appropriate type of transfer in Indonesia. Employing Propensity Score Matching (PSM), this study measures the impacts of this transition on the probability of falling below the poverty line and difficulties in accessing food and nutrition. This study uses a highly credible dataset from the National Socioeconomic Survey (SUSENAS) 2018, comprising information from 107,306 beneficiaries of both schemes in its samples. By assigning both treated and control groups from the beneficiaries of BPNT and Rastra respectively, this study seeks to take advantage of the similarities between both groups in certain socioeconomic characteristics, thus minimizing potential selection bias. To ensure further comparability between the two initiatives, samples of this study are restricted to those living in provinces where both programs are operational, primarily in Java and Sumatera Island.

The finding indicates that BPNT is less effective than Rastra in improving household welfare and access to food and nutrition. It is also evident that the negative impacts are even more pronounced in Java and rural areas, specifically among households whose heads are less educated. The finding contributes to the literature on the impact evaluation of cash versus voucher assistance in developing countries, as they are derived from a unique and reliable dataset. The unique cross-sectional setup used in the model is expected to allow the estimation of the average treatment effects through a meticulous quasi-experimental design, thus avoiding the need for a costly and time-consuming method as in randomized control trials.

The rest of the study is organized as follows — section 2 reviews the literature on the context of social protection in Indonesia. Section 3 describes the

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dataset and variables used for the analysis. Section 4 introduces the research questions, the model, and the empirical and identification strategy applied to answer the research questions. The main results, robustness check, and the effect of heterogeneity are described in section 5. Finally, the last section concludes and recommends policy implications.

2. Literature Review

2.1. Social Protection System

In the 21st century, social protection plans are growing globally, with countries integrating or coordinating social assistance, insurance, and labor market programs.10 The process begins with a social protection strategy, which aims to improve coverage. In 2015, 77 developing nations had established a social protection strategy, with 31 considering or in the process of creating one (Honorati, Gentilini & Yemtsov 2015).

In Indonesia, the term social protection first appeared as a response to the economic crisis that hit the country around 1997–1998. In the early stages of development, the social protection system in Indonesia focused on mitigating risks and fulfilling the basic needs of individuals. It was then developed into a program to increase human resource capacity and protection of other productive assets, seeking to avoid inter-generational poverty traps (Handayani 2010). Thus, the social protection system includes social assistance programs and other social insurance funds financed by the state budget. The former provides financial support to certain groups of people such as the poor, people with disabilities, and the elderly. The latter includes programs that manage uncertainties as a result of unemployment, illness, work-related accidents, natural disasters, and aging. All of these are funded through both conditional and unconditional transfers in the form of cash and goods, including temporary subsidies (ibid).

According to the World Bank (2017), the social protection system in Indonesia currently consists of contributory schemes, constituting health insurances and employment insurance programs, and non-contributory schemes, involving social assistance programs financed by general tax revenue. The latter includes Rastra and BPNT that will be discussed in greater detail in the following section.

2.2. Rastra and BPNT

The food assistance program in Indonesia has undergone significant reform since its inception. The Rastra program was initially known as Raskin and implemented in the 2009–2014 period as a continuation of the Special Market Operation (OPK, *Operasi Pasar Khusus*). Under this rice assistance program for the poor, the government distributed subsidized rice to 15.5 million poor households. Each household received a monthly allocation of 15 kg of rice per Family Beneficiary (KPM) at a unit price of IDR 1,600/kg through the village heads or community leaders. Since 2015, the program has changed its name to Rastra while maintaining its primary target of supplying subsidized rice to 15.5 million poor households at the bottom 25 percent of income earners (Timmer, Hastuti & Sumarto 2017). The procurement of rice for Rastra is entrusted to the state-owned National Logistics Agency (Bulog), which subsequently delivers rice to more than 50,000 local distribution points below market prices. This mechanism of stabilizing domestic rice price intends to protect households from food insecurity. By design, the transfer of Rastra is supposed to significantly improve household prosperity, first and foremost in food-insecure areas where access to a consistent supply of reasonably priced foodstuffs through regular markets is unreliable (World Bank 2017).

However, in practice, Rastra has suffered from severe drawbacks, one of which is the dilution of benefits. For instance, there have been substantial discrepancies between the value of the assistance reported by beneficiaries through SUSENAS and the actual quantity of rice procured by the government. In certain cases, households are required to purchase the rice at higher prices than the initially promised prices. In addition to this disparity, inclusion and exclusion errors as well as other delivery-related issues eventually diminish the effectiveness of Rastra (World Bank 2017).

In response to the aforementioned issues, e-voucher is introduced to replace Rastra, as stipulated in the Presidential Regulation Number 63 of 2017 on the Disbursement of Non-Cash Social Assistance. Thus, starting in 2017, Rastra has transformed into BPNT. Under this system, poor households previously entitled to Rastra will receive IDR110,000 per KPM per month. This amount is transferred through an electronic banking account and exclusively designated to purchase food at e-warong or other food stalls in collaboration with Bank Himbara (BRI, BNI, Mandiri, and BTN).

During its initial phase in 2017, BPNT could only reach 1.2 million KPM of the targeted 1.4 million KPM across 44 cities in Sumatera and Java Island where functional rice markets are available. In addition to rice, BPNT can be used to acquire other staples such as sugar, oil, and eggs. BPNT was implemented in all regions of Indonesia with a target of 10 million KPM in 2018. By 2019, the program aspired to reach 15.6 million KPM. The remaining beneficiaries, mostly those living in remote areas, continue to receive Rastra, which is shifted from a subsidy scheme to a food social assistance (in-kind transfer). Collectively, these food programs are considered as the largest income transfer program in Indonesia, with allocated spending of 0.18 percent of GDP (TNP2K 2018).

The shift of transfer mechanism from food subsidies (Rastra) to non-cash food assistance (BPNT) is a strategic initiative taken by the Government to ensure that food assistance reaches its intended target at the right price, quantity, time, quality, and administration, and promotes more balanced nutrition as needed by the beneficiaries. Therefore, this change is expected to improve the distribution mechanism of food assistance, addressing issues regarding its effectiveness in targeting and reaffirming it as a pivotal instrument of social protection, particularly in fostering food security. Moreover, BPNT is expected to empower the poor through e-warong and provide the poor with access to financial services. It is also anticipated to promote the effectiveness and efficiency of assistance programs in terms of targeting and to deliver optimal benefits for poverty alleviation and gap reduction.

The approach to determine beneficiaries is consistent in both programs. They are selected from the bottom 25 percent of income earners as determined by the Unified Database (UDB, *Basis Data Terpadu*). Developed in 2005, UDB is an electronic database which contains social, economic, and demographic information through a survey by the Statistics Indonesia (BPS), namely Socioeconomic Data Collection (PSE). This survey includes basic information on 19 million households in the bottom 30 percent of the income distribution. The database was updated using surveys conducted in 2008 and 2011 by the National Team for the Acceleration of Poverty Reduction (TNP2K) in collaboration with BPS, covering approximately the poorest 40 percent of the population, or an estimated 96.4 million individuals.

Initially, poverty was classified based on 14 non-monetary variables, from which a weighted welfare index for each individual is calculated. Subsequently, a Proxy Means Test (PMT) is applied to obtain household scores, which gradually improves the precision of targeting. To enhance the accuracy of UDB and involvement at a local level, an update was undertaken in 2015. In addition to PMT, a Public Consultation Forum (*Forum Kosultasi Publik*, FKP) is established to improve program targeting, in which the teams at the local level (villages/subdistricts) are requested to update the list of beneficiaries via a series of regular community meetings.

Another approach proposed to reduce inclusion and exclusion errors is self-targeting (Alatas et al. 2016). This method allows individuals to identify themselves as eligible for assistance. However, they have to undergo an initial assessment and fulfill the requirements to be included in the UDB list. The official beneficiary list and quota comprising 40 percent of the poorest as well as the management of the database fall under the authority of the Ministry

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of Social Affairs.

3. Method

3.1. Data and Variables

To examine the impact of the transition from Rastra to BPNT, this study relied primarily on the data from SUSENAS of March 2018. It is a multi-purpose household survey that has been administered biannually (every March and September) in Indonesia since 1979. Its probability sample design allows for representative estimations at the district level, covering approximately 300,000 households in all districts in Indonesia. In summary, the sample was specified using a three-step approach: (1) selecting 25 percent of the total census blocks using probability proportional to size; (2) determining a specific number of census blocks in each district, by urban and rural areas, using systematic sampling; and (3) deciding households through the systematic sampling with implicit stratification of the highest level of education attained by the household head[1].

SUSENAS of March 2018 gathered relevant data for measuring the intended outcomes and delivery of Rastra and BPNT in 2017. These include access to food and nutrition, food quality, and the use of transfers. In 2017, a total of 104,916 households obtained Rastra and 2,492 received e-vouchers (BPNT). Due to the readiness and availability of banking infrastructure, BPNT is only implemented in select areas of the country, mostly in Java and Sumatera. To ensure higher comparability between the treatment and the control group, the analysis was therefore restricted to locations where both Rastra and BPNT are implemented. It reduced the sample size to 65,890 beneficiary households[2]. In this study, the treatment group comprises households receiving BPNT, while the control group consists of households receiving Rastra, accounting for 2,481 and 63,409 households, respectively. Table 1 discloses variable summary statistics for analyzing the impact of the transition in food programs, in which the sample is divided into two groups: those receiving BPNT (the treatment group) and those receiving Rastra (the control group).

This study utilized three dependent variables of interest, comprising expenditure above the poverty line (PCEXP), access to nutrition (nutacces) and access to food (FoodAccess). The first dependent variable is a dummy indicating if a household is classified as poor or not. This dummy is constructed by comparing the monthly per capita expenditure of the household to the district-level poverty line[3]. This variable is assigned a value of 1 (=above poverty line) for households with monthly expenditure equal or more than the district poverty line; otherwise is 0. Observed from the summary statistics presented in Table 1, both Rastra and BPNT cover mostly the non-poor households, i.e. more than 80 percent of beneficiaries from each program are households whose monthly expenditure exceeds the poverty line.

For the second outcome, namely access to nutrition, a dummy variable is constructed using a question item in SUSENAS, which seems able to disentangle the outcomes between Rastra and BPNT. A member in each household, either the head of household, the spouse, or children aged 15 or above, was questioned about having difficulties in accessing healthy and nutritious food because of lack of money or other resources during the last year. This outcome is assigned a value of 1 if the answer is no, which implies no difficulty in accessing nutrition, otherwise is 0. As displayed in Table 1, the majority of BPNT and Rastra beneficiaries do not encounter any difficulties in accessing nutrition, as proven by the mean exceeding 0.5. However, the

[1] More detailed information on the survey, sampling design and allocation of census block are available at: http://microdata.bps.go.id/mikrodata/index.php/catalog/653/related_materials (in Bahasa).

[2] SUSENAS does not cover information up to family level; thus, the information about beneficiaries presented in this study is at household level.

[3] The district-level poverty line is obtained from BPS-Statistics Indonesia website for the year 2018. It is drawn using a feature of dynamic table, which are available at: https://www.bps.go.id/site/pilihdata.html (in Bahasa).

descriptive statistics do not necessarily mean that the outcomes are comparable or generalizable to the broader population. An inferential method is required to prove statistical significance.

The third outcome, namely access to food, derives from the same block as the former one. However, in this regard, difficulty in accessing food is measured using all questions within the "access to food" section, unlike the previous outcome focusing only on access to nutritious food. Consequently, it is inevitable that a certain level of overlap occurs between this outcome and the previous one, as they both utilize the same set of questions. Similarly, the dummy variable is assigned a value of 1 if the answer to all eight questions in that section is no, signifying no difficulty in accessing food, otherwise is 0. The inclusion of this outcome is intended to determine which of the two initiatives is more effective in improving food access for people. Table 1 displays the mean value of this variable, which exhibits a close proximity at 0.6.

In addition to the aforementioned three outcomes, this study incorporated a comprehensive set of covariates that reflect both the socio-economic conditions of households and the socio-demographic characteristics of their heads. The former includes dwelling conditions, mainly used when applying the PMT approach, expressed as a dummy variable assigned a value of 1 for non-poor condition, and 0 otherwise. These conditions encompass house ownership; type of roof, wall, and floor; toilet facility; water source; main source of lightning; and number of properties (including car, television, air conditioning system, and others). Furthermore, this study controlled for access to financial institutions (i.e. whether household members have access to banking services). This study also seeks to compare household locations, specifically distinguishing between Java and non-Java regions, as well as between urban and rural areas. The other set of covariates pertains to socio-demographic characteristics of the household heads, which involve age, gender, latest education, and working status. A more detailed description on the variables utilized in this study is presented in Table A1 due to lack of space (see Appendices).

3.2. Empirical Strategy

As previously mentioned, BPNT requires well-functioning rice markets and accessible banking infrastructure. Therefore, the BPNT implementation in 2017 was concentrated in 44 districts located mostly in Java and Sumatra Island, whereas the other districts continued to receive Rastra. Considering the absence of the randomized assignment, a meticulous and sophisticated approach is imperative to assess the effectiveness of the programs against a counterfactual circumstance (Ravallion 2007).

Following the Roy-Rubin-model (Roy 1951; Rubin 1974), this study adopts the potential outcome approach as the standard framework for impact evaluation, which mainly concerns itself with individuals (or in this context households), treatment, and potential outcomes. $\mathrm{D_i}$ denotes a binary treatment indicator whose value equals to 1 for beneficiary and 0 otherwise while $\mathrm{Y_i}\ (\mathrm{D_i})$ represents the potential outcomes for each household i. The treatment effect for each household i thus can be written as:

$$\tau_{\mathrm{i}} = \mathrm{Y_i}(1) - \mathrm{Y_i}(0) \tag{1}$$

One fundamental challenge in the evaluation is that only one potential outcome can be observed for each household i, rendering the above estimation impossible. An alternative method for estimating the treatment effect is employing a naïve approach or *Ordinary Least Squares* (OLS). However, this approach may raise several problems in terms of internal validity due to selection and/or heterogeneity bias supposing the treatment is correlated with the error term. Additionally, issues regarding external validity may arise due to lack of generalizability of the estimated treatment effect. Another alternative parameter of interest is the Average Treatment Effect (ATE) which can be written as follows:

$$\tau_{\mathrm{ATE}} = \mathrm{E}[\mathrm{Y_i}(1) - \mathrm{Y_i}(0)] \tag{2}$$

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Table 1. Summary Statistics

Variable	Control			Treatment		
	Obs.	Mean	Std.Dev	Obs.	Mean	Std.Dev
Outcomes						
Above poverty line	63,409	0.889	0.314	2,481	0.852	0.354
Access to nutrition	63,409	0.813	0.390	2,481	0.794	0.404
Access to food	63,409	0.652	0.476	2,481	0.640	0.480
Covariates						
ln (per capita expenditure)	63,409	13.401	0.517	2,481	13.547	0.478
House ownership status	63,409	0.115	0.319	2,481	0.328	0.470
Roof type	63,409	0.375	0.484	2,481	0.374	0.484
Wall type	63,409	0.381	0.486	2,481	0.168	0.374
Floor type	63,409	0.486	0.500	2,481	0.331	0.471
Toilet Facility	63,409	0.449	0.497	2,481	0.330	0.470
Water source	63,409	0.340	0.474	2,481	0.069	0.253
Main source of lighting	63,409	0.170	0.375	2,481	0.098	0.297
Number of properties	63,409	2.046	1.168	2,481	1.978	1.213
Head of HH's age	63,409	50.535	13.602	2,481	51.480	11.383
Head of HH's marital status	63,409	0.796	0.403	2,481	0.802	0.398
Head of HH's gender	63,409	0.821	0.383	2,481	0.821	0.383
Head of HH's education	63,409	0.877	0.328	2,481	0.816	0.388
Head of HH's working status	63,409	0.852	0.355	2,481	0.827	0.379
Access to financial institution	63,409	0.793	0.405	2,481	0.791	0.407
Java	63,409	0.550	0.498	2,481	0.777	0.417
Urban	63,409	0.287	0.452	2,481	0.940	0.237

Source: SUSENAS of March 2018. Control and treatment groups include all households receiving Rastra and BPNT, respectively.

The further challenge in estimating ATE is that both counterfactual outcomes need to be constructed.

Various ways are available to estimate counterfactuals. This study employed PSM, one of matching procedures that models the likelihood of participating in the treatment. Matching methods allow the counterfactual or the control group to be developed based on the similarities of observable characteristics with the treatment group. Supposing differences in participation can be assumed to be solely dependent on the differences in observable characteristics, and with large available counterfactuals, one can measure the average treatment effect without randomized assignment, as in the case in observational studies (Khandker, Koolwal & Samad 2010). Specifically, PSM estimates the single propensity score of each individual $\mathrm{P(X) = Pr(T = 1|X)}$, by which the participants are then matched to non-participants (Rosenbaum & Rubin 1983). The advantage of using the propensity score is the mitigation of the 'curse of dimensionality' which arises from incorporating an excessive number of observable characteristics. In this study, the propensity score is estimated using the probit function.

To ensure the validity of the PSM estimate, one identification strategy is to satisfy the *unconfoundedness assumption*, also known as the *Conditional Independence Assumption* (CIA). It implies that, conditional on a set of observed covariates, treatment assignment is independent of potential outcomes. Based on the propensity score, the CIA can be written as:

$$\mathrm{Y(0), Y(1) \perp\!\!\!\perp D|P(X), \quad \forall X} \tag{3}$$

In addition to CIA, a further requirement is the *overlap condition or common support*, denoted as $0 < \mathrm{P(D_i = 1|X)} < 1$. This assumption ensures that individuals with the same X have a positive probability to either participate or not participate in the program (Heckman, LaLonde & Smith 1999 cited in Caliendo & Kopeinig 2008). Once these two assumptions hold, the PSM estimator can be specified as the mean difference of outcomes, weighted by the propensity score distribution of the treated group.

Apart from selection and heterogeneity bias, this identification strategy may still encounter the endogeneity issue due to self-selection. It poses a serious problem supposing a self-targeting approach is thoroughly implemented in determining BPNT beneficiaries. However, it can be assumed that it is unlikely to be the case considering various requirements to be fulfilled to be considered eligible for the program, in which the authority to validate belongs to the Ministry of Social Affairs. Another source of endogeneity potentially stems from omitted variables. To deal with this issue, this study utilized a rich set of covariates, consisting of the socio-economic indicators of households and the socio-demographic characteristics of the heads of the households.

To check the robustness of the estimated treatment effects, this study applied other matching estimators, which involve Nearest Neighbor Matching (NNM) and Inverse-Probability Weighting and Regression Adjustment (IPWRA). NNM is a nonparametric method that matches treated with untreated units based on the closest *Mahalanobis* distance, which is calculated between pairs of observations based on the values of covariates X. On the other hand, IPWRA is preferred due to its "doubly robust" nature. It correctly specifies models for both treatment and outcome variables, which in this regard is probit. This estimator combines regression adjustment and weighting procedure to estimate missing counterfactuals.

4. Results and Analysis

4.1. Impacts of Food Reform on Measures of Household Well-Being

As previously mentioned, the reason behind treatment assignment, i.e. BPNT as treatment and Rastra as control, is to ensure comparability between treatment and control groups, thereby helping minimize bias in baseline data. Both treatment and control groups are expected to demonstrate similar socio-economic and demographic characteristics as they are drawn from the same bottom 40 percent of the income distribution and located in the same regions. However, the balance test conducted prior to matching, as displayed in Table A2 (see Appendices), reveals no evidence of covariate balance across the two groups. Simply by regressing each covariate on the treatment variable, it is evident that nearly all of household characteristics exhibit significant differences between the control and treated groups, except for per capita expenditure, house ownership, roof type, age of the household head, marital status, gender, and financial access. It implies that estimated treatment effects may not be as straightforward as those under the naïve approach. Nonetheless, this section will still present the estimated impacts using OLS, both with and without covariates, merely to provide an initial view of the reform impacts.

Table 2 portrays the estimated impacts on three measures using the naïve approach in column (1) and the unconfoundedness approach (OLS with covariates) in column (2). The findings reveal negative effects of the transition from Rastra to BPNT, suggesting that Rastra is more effective in increasing the welfare of the people as well as access to food and nutrition. However, these estimates are not consistent since conditional exogeneity assumption does not hold. The unbalanced control variables indicate the presence of potential confounding factors that influence the outcomes in the absence of treatment. Therefore, the magnitude of the impacts will then be observed from the next result using the matching procedure.

Table 3 displays the results derived from PSM. As previously explained, this method is employed to select the counterfactual for each beneficiary household based on propensity scores. Similar to the previous results obtained through the naïve and unconfoundedness approaches, the estimates generated by PSM suggest adverse effects of transition from Rastra to BPNT on well-being measures. Households receiving BPNT are less likely to have expenditure above the poverty line and also less likely to obtain access to food and nutrition compared to

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Table 2. Estimated Treatment Effects using the Naïve and Unconfoundedness Approaches

Variables	PCEXP		nutacces		FoodAccess	
	(1)	(2)	(1)	(2)	(1)	(2)
treatment	-0.037***	-0.086***	-0.019**	-0.043***	-0.012	-0.035***
	(0.007)	(0.006)	(0.008)	(0.008)	(0.010)	(0.010)
1) Household socio-economic cond.		Yes		Yes		Yes
2) HeadHH socio-demographic cond.		Yes		Yes		Yes
_cons	0.889***	-3.653***	0.813***	-0.275***	0.652***	-0.722***
	(0.001)	(0.042)	(0.002)	(0.043)	(0.002)	(0.052)
R^2	0.00	0.30	0.00	0.08	0.00	0.08
N	65,890	65,890	65,890	65,890	65,890	65,890

Note: * p<0.1; ** p<0.05; *** p<0.01.
Estimated standard errors in parentheses.
PCEXP represents households with per capita expenditure above poverty line, while NutAccess and FoodAccess represent households with access to nutrition and food, respectively.
Estimation using OLS.

those receiving Rastra. In specific comparison to Rastra, receiving BPNT reduces the probability of rising above the poverty line by 12.1 percentage points and having access to food and nutrition by 15 and 11.7 percentage points, respectively. These estimates are significant, tested at 1 percent level.

Table 3. Estimated Average Treatment Effects Using PSM

	PCEXP	Nutacces	FoodAccess
r1vs0.treatment	-0.121***	-0.117***	-0.150***
	(0.043)	(0.041)	(0.042)
N	65,890	65,890	65,890

Note: * p<0.1; ** p<0.05; *** p<0.01.
Estimated standard errors in parentheses.
PCEXP symbolizes households with per capita expenditure above the poverty line, while NutAccess and FoodAccess represent households with access to nutrition and food, respectively.
Propensity scores are estimated using probit.

Prior to delving into a more detailed explanation of the results, it is essential to ensure the validity of PSM by observing its properties, including overlap and balanced covariates. Figure A1 (see Appendices) illustrates the estimated density of predicted probabilities to receive BPNT for BPNT household beneficiaries (treatment group) and Rastra beneficiaries (control group). The two estimated densities have the largest share of their respective masses in regions where they overlap each other, shown by considerable common support. It confirms that overlap assumption is acceptable.

In addition, a balancing test is conducted and compared between before and after the matching procedure. In this study, the assumption is examined using balance plot and covariate balance summary, as demonstrated in Figure A2 and Table A3 (see Appendices). The results from the matched sample indicate that matching on the estimated propensity score remarkably balances the covariates. The standardized differences are all close to zero, and the variance ratios are all close to one. Thus, it can also confirm that covariates are balanced across the treatment and control groups using PSM, implying that the estimated impacts using this method are sufficiently valid.

4.2. Robustness Check

This section describes a robustness test for the estimated impacts using other matching procedures. As previously mentioned, this study applied IPWRA and NNM for comparison with the PSM results. The results are presented in Table 4.

The table illustrates how the estimates change across different methods. The NNM method reveals the smallest impacts of program transition on the outcome measures of households. However, the overall impacts appear consistent in terms of both direction and magnitude. Thus, it is confirmed that the estimates are robust as those obtained through the OLS estimation.

Table 4. Robustness Check Using Other Matching Methods

Method	PCEXP	nutacces	FoodAccess
PSM	-0.121***	-0.117***	-0.150***
	(0.043)	(0.041)	(0.042)
IPWRA	-0.139***	-0.102***	-0.164***
	(0.011)	(0.027)	(0.029)
NNM	-0.034***	-0.068***	-0.074***
	(0.012)	(0.025)	(0.026)

Note: * p<0.05; ** p<0.01.
Estimated standard errors in parentheses.
PCEXP denotes households with per capita expenditure above the poverty line, while NutAccess and FoodAccess denote households with access to nutrition and food, respectively.

4.3. Heterogeneity Analysis

This section provides the estimation across subgroups of the beneficiary population as it is suspected that different impacts exist across household characteristics. The heterogeneity test focuses on four different household indicators, including gender and education level of the head of household as well as whether the household is located in Java and in the urban area. These variables are displayed as dummies, and the estimation is separately conducted for the dummies at values equal to zero and one. The result is displayed in Table 5.

The table demonstrates that the transition of the food assistance program provides significant differential declines in per capita expenditure, access to food, and access to nutrition in certain groups of households. The negative impact of the program transition on per capita spending appears to be stronger for households with less-educated heads, as well as those located outside Java or in the rural areas. Similarly, regarding access to nutrition, the negative impact is considered strong in rural areas, Java, and households with less-educated heads. Meanwhile, in terms of food access, the transitioning program negatively affects households whose heads are male or less educated. The negative effect is also considered strong in Java and rural areas.

The next task is to explain the reasons behind the negative effects of transitioning from cash to voucher transfers on household welfare. Firstly, these results may align with the descriptive statistics provided in the previous section. The average values of outcome for Rastra as the control group are shown to be larger than those of BPNT. With regards to per capita expenditure, receiving voucher transfer through BPNT implies that households will have less cash than they will have received under Rastra. Moreover, the results are consistent with the predictions of economic theory, which suggest that households will benefit more from cash compared to in-kind or voucher transfers1. Upon closer examination of SUSENAS data, it has been reported that most people are unaware of the amount of money they receive from BPNT. Several people who are aware of the amount do not use it to purchase food as intended by the program[4]. It suggests that lack of information and low enforcement contribute to the ineffectiveness of the program.

Another explanation may relate to the selection of the first outcome variable. Since expenditure is utilized to estimate poverty in this context, it is unsurprising that those receiving cash assistance will have higher expenditure, thus surpassing the poverty line. It underscores a potential avenue for future revision, to consider income rather than spending as a benchmark for poverty.

Nonetheless, this study does not intend to definitively label the reform as a failure. It is admitted that impacts may take time to materialize. Since BPNT has been recently implemented, it may be premature to conclude that BPNT is not effective. Additionally, there are several limitations to consider. Regarding the choice of variable, it is recommended for future research to explore using income rather than spending as a benchmark for poverty. Furthermore, it will be beneficial to consider wider economic impacts, such as on supporting local markets or production. This may extend beyond the scope of this evaluation and require specific specialized studies. Moreover, the utilization of panel data in future research may provide a better understanding

[4]Based on author's calculation using SUSENAS 2018 data.

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DOI: 10.47291/efi.2023.07

Table 5. The Impacts of Transition from Rastra to BPNT Across Subgroups

Variables	Value	Observation	PCEXP		NutAccess		FoodAccess	
			τ	SE	τ	SE	τ	SE
HeadHH is male	1	54,100	-0.088	0.056	-0.085	0.062	-0.152	0.039**
	0	11,790	-0.068	0.089	-0.050	0.084	-0.067	0.107
HeadHH is less educated	1	57,642	-0.098	0.032**	-0.107	0.043*	-0.170	0.033**
	0	8,248	-0.109	0.099	0.038	0.068	0.000	0.097
HH is in Java	1	36,790	-0.073	0.034*	-0.181	0.036**	-0.148	0.046**
	0	29,100	-0.107	0.044*	-0.071	0.076	-0.120	0.060*
HH is in the urban areas	1	20,519	-0.082	0.011**	-0.032	0.013*	-0.008	0.015
	0	45,371	-0.076	0.035*	-0.093	0.044*	-0.203	0.050**

Note: * p<0.05; ** p<0.01.
τ symbolizes estimated average treatment effects.
PCEXP denotes households with per capita expenditure above the poverty line, while NutAccess and FoodAccess denote households with access to nutrition and food, respectively.
Estimation uses PSM method.

as it will allow more sophisticated methods. Finally, future evaluations can benefit from employing randomized control trials to reveal the real impacts of the ongoing programs.

5. Conclusion

This study contributes to the literature on the impact of cash versus voucher type of assistance on poverty alleviation and food security in developing countries. The unique cross-sectional setup utilized in the model is expected to allow the estimation of average treatment effects through meticulous quasi-experimental design. It is revealed that BPNT is less effective compared to Rastra in improving household welfare and access to food and nutrition, which is consistent with economic theory. It is also evident that the impacts of the transition from cash to voucher are more adverse in Java and rural areas than in non-Java and urban areas. This trend is also observed among households whose heads have a low level of education.

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https://scholarhub.ui.ac.id/efi/vol69/iss2/2
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Appendices

Table A1. Description of Variables

Variable Name	Type	Description
Outcomes		
Above poverty line	Dummy	1= above district-level poverty line
Access to nutrition	Dummy	1= no difficulty in accessing nutrition
Access to food	Dummy	1= no difficulty in accessing food at all
Covariates		
ln (per capita expenditure)	Continuous	Monthly expenditure (log transformed)
House ownership status	Dummy	1= other than private/official house
Roof type	Dummy	1= other than concrete/tile
Wall type	Dummy	1= other than concrete/plastered woven
Floor type	Dummy	1= other than marble/granite/ceramic, Parquet/vinyl/carpet, tile/clay tiles/terrazzo, wood/planks
Toilet Facility	Dummy	1= other than septic tank
Water source	Dummy	1= other than branded, refill, plumbed, protected well
Main source of lighting	Dummy	1= other than PLN
Source of fuel	Dummy	1= LPG3kg, kerosene, briquette, firewood, charcoal
Number of properties	Count	Row total assets ownership (excluding house)
Head of HH's age	Continuous	
Head of HH's marital status	Dummy	1= married
Head of HH's sex	Dummy	1= male
Head of HH's latest education	Dummy	1= graduated from SMP and below
Head of HH's working status	Dummy	1= working
Access to financial institution	Dummy	1= no access
Java	Dummy	1= Java
Urban	Dummy	1= urban

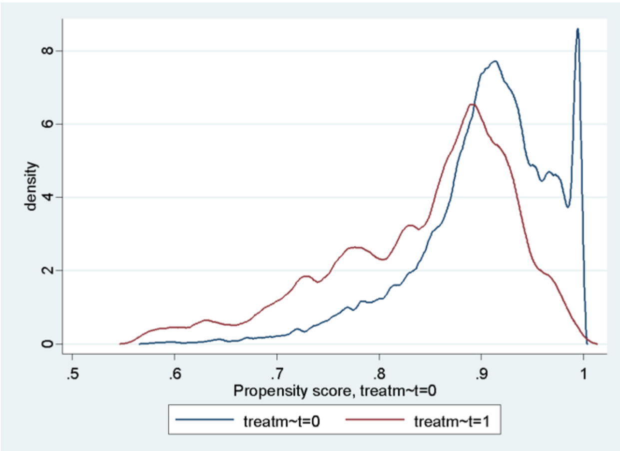

Figure A1. Test Overlap Assumption (Common Support)

Table A2. Covariates Balanced Check Before Matching

	VARIABLES	treatment	Constant	Observations	R-squared
(1)	ln_excap	0.147***	13.40***	65,890	0.003
		(0.00980)	(0.00205)		
(2)	own house	0.213***	0.115***	65,890	0.015
		(0.00951)	(0.00127)		
(3)	roof	-0.000873	0.375***	65,890	0.000
		(0.00990)	(0.00192)		
(4)	wall	-0.213***	0.381***	65,890	0.007
		(0.00775)	(0.00193)		
(5)	T_floor	-0.155***	0.486***	65,890	0.004
		(0.00965)	(0.00198)		
(6)	FecDisp	-0.119***	0.449***	65,890	0.002
		(0.00965)	(0.00198)		
(7)	water	-0.271***	0.340***	65,890	0.012
		(0.00542)	(0.00188)		
(8)	elect	-0.0718***	0.170***	65,890	0.001
		(0.00615)	(0.00149)		
(9)	assets	-0.0679***	2.046***	65,890	0.000
		(0.0248)	(0.00464)		
(10)	age	0.945***	50.54***	65,890	0.000
		(0.235)	(0.0540)		
(11)	married	0.00682	0.796***	65,890	0.000
		(0.00815)	(0.00160)		
(12)	Male	-2.65e-05	0.821***	65,890	0.000
		(0.00784)	(0.00152)		
(13)	hh_edu	-0.0613***	0.877***	65,890	0.001
		(0.00789)	(0.00130)		
(14)	h_working	-0.0256***	0.852***	65,890	0.000
		(0.00773)	(0.00141)		
(15)	Financial	-0.00229	0.793***	65,890	0.000
		(0.00832)	(0.00161)		
(16)	java	0.227***	0.550***	65,890	0.008
		(0.00859)	(0.00198)		
(17)	urban	0.654***	0.287***	65,890	0.072
		(0.00508)	(0.00180)		

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, *p<0.1

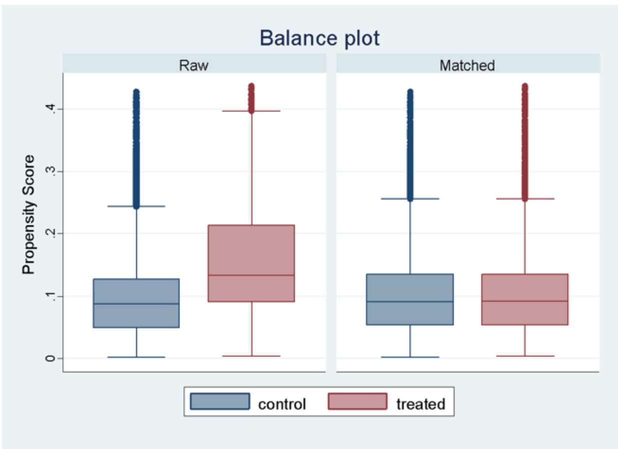

Figure A2. Balance Check Result Before and After Matching

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Table A3. Covariates Balanced Summaries Before and After Matching Using PSM

note: refitting the model using the **generate()** option

Covariate balance summary

	Raw	Matched
Number of obs =	65,890	131,780
Treated obs =	2,481	65,890
Control obs =	63,409	65,890

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
ln_excap	.2949523	.0572025	.8523578	.8887553
ownhouse	.5310665	-.0983332	2.168176	.7791998
roof	-.0018026	.0100767	.9994524	1.005068
wall	-.4917968	-.0541094	.5929706	.9689803
T_floor	-.3198673	-.0443791	.8866603	.9945893
FecDisp	-.24527	-.0210717	.8942558	.9948391
water	-.7131061	.0361581	.2861788	1.025037
elect	-.2120685	.0734533	.627122	1.12955
assets	-.0570072	-.0895487	1.07951	1.089727
age	.0753655	-.054333	.7002865	.7441973
married	.017028	.0421546	.9752724	.937386
Male	-.0000691	.0090625	1.000503	.9847928
hh_edu	-.1707247	-.0102943	1.394873	1.023305
h_working	-.0697111	.0816673	1.138362	.8393649
Financial	-.0056532	.0704933	1.008557	.8962571
java	.4945127	-.1087241	.7009677	1.0134
urban	1.810274	.0519375	.2743446	1.04007