Manuscript JESP - Subsidized Health Insurance Impact Among the Poor

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Subsidized Health Insurance Impact Among the Poor:
Evidence on Out-of-Pocket Health Expenditures in Indonesia

Abstract
Universal Health Care (UHC) in Indonesia, named the National Health Insurance (*Jaminan Kesehatan Nasional* - JKN), has been running since 2014. JKN was predicted to be the largest UHC program in the world. Under JKN, the poor get free health services by the cashless method through a sub-program called Contribution Assistance Recipients (*Penerima Bantuan Iuran* - PBI). Unfortunately, JKN faced several failures to cover the program's expenditures within years. Within the current dynamics, was PBI as part of JKN still effectively helping the poor? We examined the effectiveness of the PBI program by measuring differences in out-of-pocket health expenditures for the poor who used PBI and those who did not. We incorporated secondary data from National Socioeconomic Survey (SUSENAS). The dataset executed by using Propensity Score Matching (PSM) methodology. We used health expenditures and socioeconomic parameters such as income, education, and gender from the 2017 and 2018 SUSENAS data. We found in year 2017 the total health expenditures of the PBI beneficiaries were lower that the non-beneficiaries. Nevertheless, by merged all two years data, similar with year 2018, we found general pattern that PBI participants' total health out-of-pocket payments were bigger than the non-participants. Health expenditures such as medicine, traditional practitioners, and others, were expenditure classifications which PBI beneficiaries had lower expenses than non-beneficiaries in 2017. Therefore, the effectiveness of the UHC subsidy program for the poor in Indonesia has not only inconsistently ineffective between years of implementation, but also has not been effectively distributed for all variations of health expenditure types.
Keywords: Indonesia, PBI, Poverty, Propensity Score Matching, Universal Health Care
JEL Classification: C31, C38, C46, H51, I13, I38

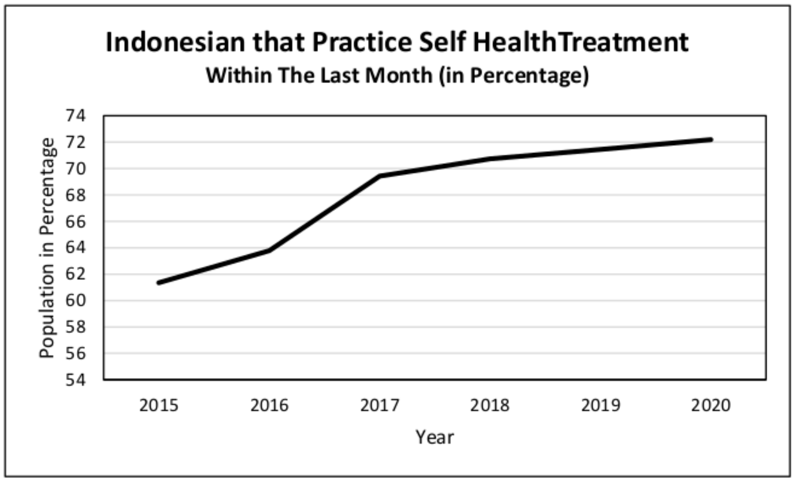
Introduction

Universal health coverage (UHC) has been seen as a new system in many countries (McKee et al. 2013). The main objectives associated with UHC were usually to ensure that everyone can access health services without undergoing financial difficulties and to reduce direct payments from households at the time of health services use. Nonetheless, UHC implementation can be quite challenging, particularly for the poor who cannot afford healthcare expenses due to low and unstable income.

The government's subsidization that pays the health insurance coverage on behalf of the poor can be one of the most effective ways to eradicate health access inequality. Meanwhile, in Indonesia's UHC system, a particular program was allocated for low-income people named Contribution Assistance Recipients (*Penerima Bantuan Iuran* - PBI). The PBI program was a sub-program under the general UHC program in Indonesia called National Health Insurance (*Jaminan Kesehatan Nasional* – JKN). In the initial stage, PBI was designed for people living in poverty to get the third class of national insurance services for free in Indonesia. However, during the implementation, PBI faced obstacles similar to UHC in other countries. Therefore, it was crucial to investigate whether this program was effective enough to reduce the health expenditures of the poor or not.

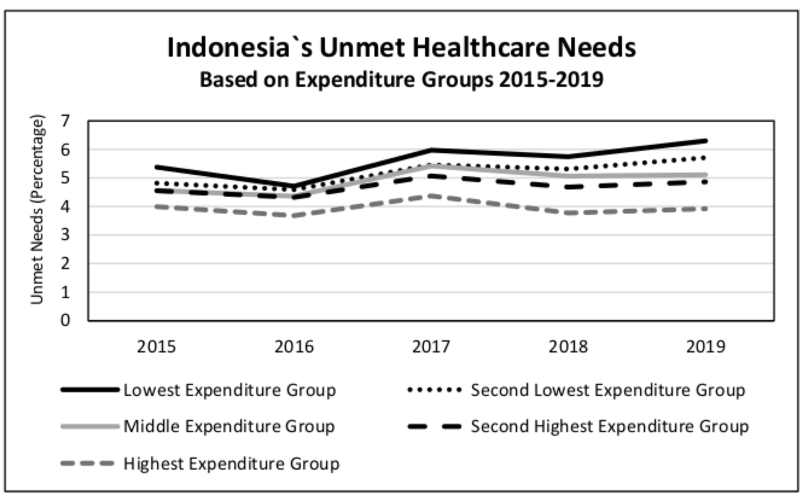
Apart from the fact that it affected many people's lives, the topic of PBI was also essential to be evaluated for several reasons. First, it was due to the increased trend of unmet health care needs within ten years in Indonesia. Furthermore, according to the Indonesia National Bureau Survey, it was found that the lowest income group had the highest level of unmet health care needs. Secondly, the trend of poverty in Indonesia has been seemingly constant for the past ten years; thus, PBI will still be needed considering the people living in poverty will have a high probability of still existing in the next following years. Finally, this was due to the deficit of the BPJS program that has been occurring for years, thus having the probability of hindering the access and effectiveness of PBI for the poor.

Figure 1 The population that Practice Self Health Treatment Within the Last Month



Source: Indonesia Statistics database. Date Accessed: January 31, 2021.

Figure 2 Indonesia's Unmet Healthcare Needs According to Expenditure Group



Source: Indonesia Statistics database. Date Accessed: January 31, 2021.

As Aji et al. (2013) examined, the government-covered health insurance for the poor in Indonesia in the past, executed subsidized health insurance for the low-income population. In comparison, other studies focused more on different classifications of the sample objects, such as general health care coverage insurance for maternal services, which focused more on inequality eradication, or one that focused more on children's healthcare (Anindya et al. 2020). Inter-country and inter-sector comparative insurance studies have also been conducted related to Indonesia's healthcare system (Ramesh 2014).

Various expenditure types of the healthcare system in Indonesia were also examined, either focusing on general out-of-pocket expenses in the past program (Aji et al. 2013), catastrophic insurance expenditure for the general population (Situmeang and Hidayat 2018). The results of health insurance world studies intend to be very varied. In welfare point of view, the results showed contrary positive and negative directions. Ramesh's (2014) comparative study also asserted that the Philippines' health insurance program for the poor has low effectiveness and is worse than Indonesia's. In the United States, people are relatively sensitive to price. People would be less inclined to have insurance if there was an increase in premium for both private and public insurance (Guy et al. 2012).

Our research can fill in the gap from previous literatures by provided several actions. Firstly, this research examined the effectiveness of most updated health care subsidized program in Indonesia (PBI) which was still rare up to today in literatures. Secondly, unlike other Indonesia subsidized insurance literatures, instead of investigating general outcome from all the observation years, in here we examined each single year outcome to gain detail result. The approach may answer whether PBI's current system was agile enough to deal with changing healthcare costs and effectively meet the health needs of the poor. Thirdly, we also put detail examination on health expense classifications, instead of only examined one general health expenditure behaviour. This expenditure classification approach can bring answer whether the program was effective enough to improve the health and prosperity of the poor according to their needs

We did several actions within this research to answer and tackle the challenges. First, we employed data from people who live under the poverty line from the National Socioeconomic Survey (*Survey Sosial dan Ekonomi Nasional* - SUSENAS) year 2017 and 2018. Next, we investigated total health out-of-pocket expenditures and all of the health expense terminals released by SUSENAS and grouped them into five specific group expenses. Considering the ascending trend of health costs, to prove the PBI program's continuous effectiveness throughout the year, we conducted research year by year to get specific insights for each year. Furthermore, we also merged the 2017 and 2018 datasets to get general outcomes within pooled years. Third, we used Propensity Score Matching methods to tackle limited accessibility to potential respondents, including those in remote areas.

The results showed varied results between different health expense types and periods. In 2017 several health terminal expenses were effectively lower under the PBI program. Nevertheless, in 2018, the PBI program showed that all kinds of health expenses reduction had no longer occurred under PBI. While the general results after merging the data for the year 2017 - 2018 showed similar results, where only certain types of health expenses are effectively reduced under PBI. Based on our findings, we suggested that the implementation of PBI needed to be adjusted actively along with the ascending trend of health costs. PBI coverage may also needed to be expanded to the few types of health expenses and broader types of health expense terminals. We hope that our study about out-of-pocket health spending behaviour can benefit the upcoming related policies and research.

Research Method

For this study, we used *SUSENAS* data year 2018 and 2017. For the pooled dataset, we incorporated 134.493 data. While for the 2017 dataset, we used 68.809 data, and 76.318 observations were used for the 2018 dataset. In practice, external factors changed between years, for instance, the standard poverty measurements, changes in healthcare prices, and others.

Table 1 Variable Definition and Descriptive Statistics for Pool Year Data 2017-2018

Variables	Definition	2017		2018	
	Outcome variables	**Mean**	**Stdev**	**Mean**	**Stdev**
Health	Total health expenditure in the last 12 months.	122993.3	96424.06	285053.4	483682.2
Medicine	Medicine expenditure in the last 12 months. (only drugs purchased at pharmacies, drugstores, etc.)	33541.01	42686.48	37841.06	89597.6
Treatment	Medical/healing services expenditure in the last 12 months (including birth costs and medicines not specified)	37699.67	55090.88	41151.27	85250.32
Preventive	Preventive expenditure in the last 12 months.	5172.759	24146.85	34402.27	121075.2
Hospital	Outpatient & inpatient costs in the last 12 months. (national & private hospital, public health center, health practitioner)	31895.08	59865.36	137119.5	397306.4
Tradpract	Traditional health expenditure in the last 12 months. (Traditional health practitioner & traditional midwife)	14684.83	40165.25	34538.82	117283.5
	Independent Variables				
Gender	1 if the gender category is man, 0 otherwise	0.489921	0.49999	0.49945	0.500003
Read	1 if the individual can read, 0 otherwise	0.973579	0.160385	0.956708	0.203516
Educ	The years of individual learn in formal education	9.729367	1.424036	9.639561	1.364651
Kapita	Monthly income of the individual	301026.2	49758.77	321146.3	54519.41

Source: SUSENAS 2017 - 2018, with further modifications. The definition of variables is mainly based on Indonesia Statistics SUSENAS. In comparison, the descriptions of the modified variables are defined based on the formulation.

$$Health_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (1)$$

$$Medicine_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (2)$$

$$Treatment_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (3)$$

$$Preventive_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (4)$$

$$Hospital_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (5)$$

$$Tradpract_{iy} = Gender_{iy} + Read_{iy} + Educ_{iy} + Kapita_{iy} \quad (6)$$

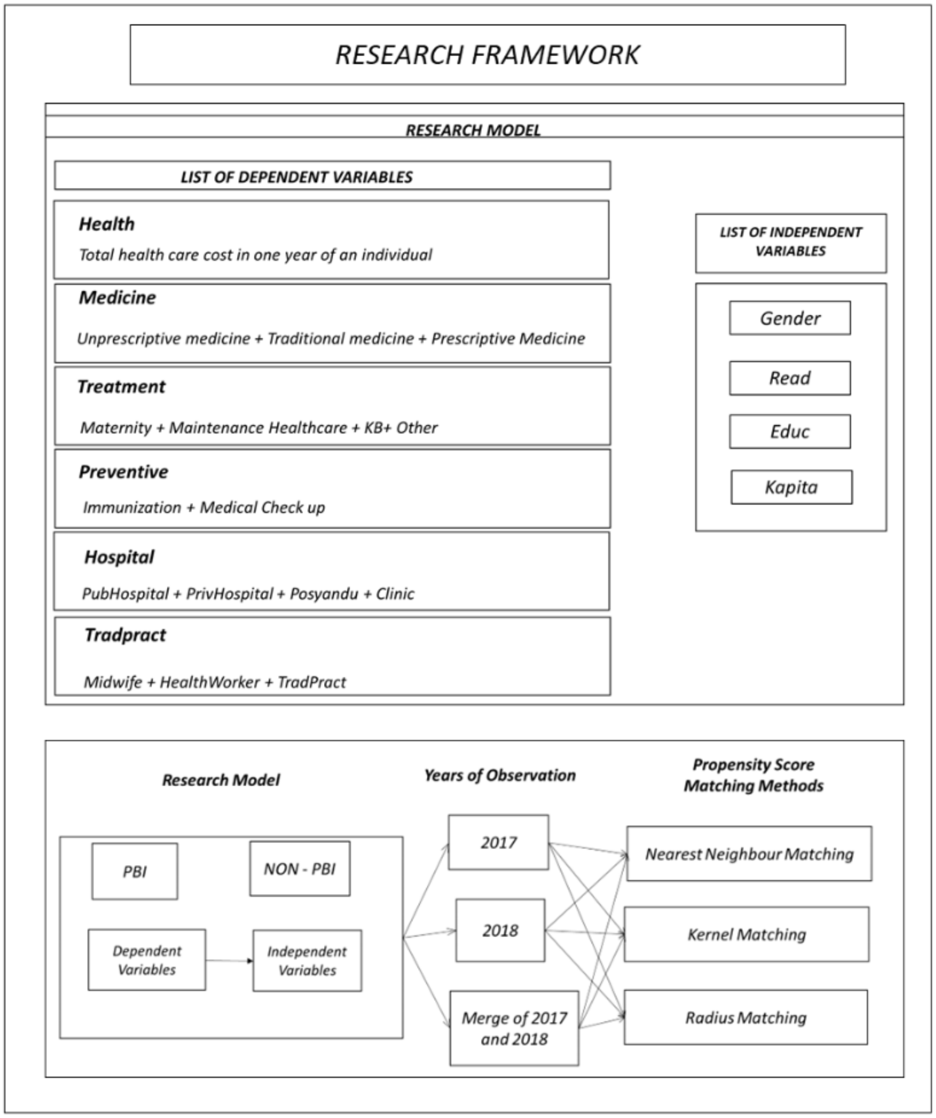
Therefore, to observe the dynamics of the spending behaviour, we specifically divided the model used into two separate years in purpose to be able to lessen the noise of socioeconomic differences and to find more similar characteristics matching observations in the same year. To understand the more significant trends within two years, we combined samples from 2017 and 2018 into one pool dataset and examined them with PSM methods. Within the research, we tried to include as much as possible of the samples to get results that were close to the natural condition.

As shown in the descriptive statistics table, there were only two variables representing categorical data, which were *Gender* and *Education*. The other variables use numerical data, namely *Educ*, *Treatment*, *Medicine, Hospital*, and *Tradpract*. From the table one, *Gender* variables mean were not vary from year to year. In other words, the proportion of men and women in Indonesia's low-income group could be considered balanced since the mean value was 0.49. The ability to read among the observation group slightly increased from year 2017 to 2018. The income per month average value was also increased by IDR 20.120. All health expenditure terminals faced an increase between the two years of observation. The total increase was IDR 162.060 on average.

The conceptual research framework of this research was depicted in figure three. There were six equations examined within three different time frames. The first time frame observed 2017 solely, the second was the single year of 2018, and the last was by creating a pool of two years datasets into one. The aims of differentiating the year of observation into different sets were to observe and understand further outcomes and patterns comparison between other times. We used Propensity Score Matching (PSM) as our main tool in this research. There were three types of PSM methods that were used in this paper, which were Nearest Neighbour Matching, Kernel Matching, and Radius Matching. Those three different PSM were used to gain comparative research outcomes.

There were sixteen different streams of out-of-pocket expenditure for healthcare made by the Indonesian population based on SUSENAS. We grouped them into six different categories. First was the *Health* variable, which consists of all total expenditure in a year, while the others were grouped based on their similarity in characteristics. Hospital and Treatment variables were two specific grouped expenses covered in the PBI program. The regressors used in this research were *Gender, Read, Educ*, and *Kapita*. Those were chosen to capture general socioeconomic conditions that were related to the health care out-of-pocket expenses and were the best to reach the balancing property needed for conducting Propensity Score Matching.

Figure 3 Conceptual Research Framework and Methodology



Notes: The figure contains the model, the data division, and the Propensity Score Matching methodology implementation in different time frames

Result and Discussion

We performed logit regression in the first phase of the PSM research stages. The purpose of doing logit regression was to determine whether there was a relationship between variables. In this regression stage, the *PBI* variable became the dependent variable, while *Gender*, *Kapita*, *Educ*, and *Read* were independent variables.

We performed three logit regressions, differentiating the 2017and 2018 time frames and 2017-2018 combined. From the regression results, most of the p-values had values below 0.05. From these results, it could be interpreted that the primary model used was reasonable. From table two, it can be seen if there were relationships between *PBI* variables and other variables. The regression results showed that the lower the community's income, the greater their tendency to participate in the PBI program. In the *Educ* variable, it could be interpreted that the lower the level of education, the greater the inclination of society to participate in the PBI program. Unlike the previous variables, the gender variable outcome in 2018 was not aligned with 2017 and the pool year. In 2018, the results showed that more women participated in the PBI program. The Read variable indicated that in 2017 people who could not read tended to participate in the PBI program. Conversely, in 2018, people who could read tend to participate in the PBI program. If the two years of observation were combined, the reading ability variable was insignificant for PBI participation.

In the second PSM stage, we calculated the propensity score for each observation. Similar to the previous step, we did three times scores calculation according to the time frame sample division as in the beginning. We also did a balancing property check while made several adjustments to the sample by removing outliers.

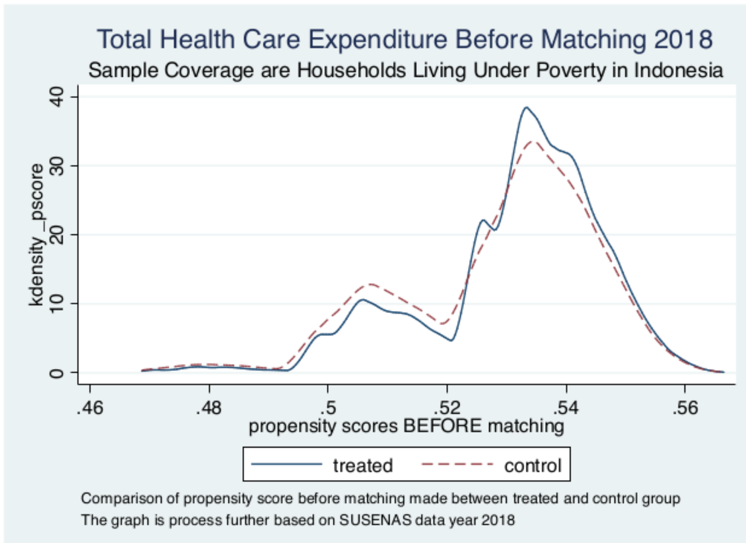
Table 2 Logit estimations of program participation (treatment = 1). Estimated coefficients for selected variables for pool data set for the year 2017-2018

Variables	**2017- 2018**	**2017**	**2018**
Gender	-0.0080559	0.0058364	-0.0288904**
	-0.0109208	-0.0153618	-0.0145164
Read	-0.0261826	-0.114404**	0.1015515***
	-0.0297683	-0.0477885	-0.0358223
Educ	-0.049556***	-0.0580424***	-0.0366072***
	-0.0039524	-0.0054803	-0.0053456
Kapita	-0.00000062***	-0.00000157***	-0.000000536***
	-0.00000011	-0.000000154	-0.000000134
Constant	0.6681671***	0.9487509***	0.5657605***
	-0.0571778	-0.0805237	-0.070912
Number of obs	134,493	68,809	76,318
LR $chi^2(4)$	198.97	242.96	74.23
Prob > chi^2	0	0	0
Pseudo R^2	0.0011	0.0026	0.0007

Source: SUSENAS 2017 - 2018, with further calculations. Notes: ***Significant at $p < 0.01$; **Significant at $p < 0.05$; *Significant at $p < 0.1$. Standard errors are in parentheses

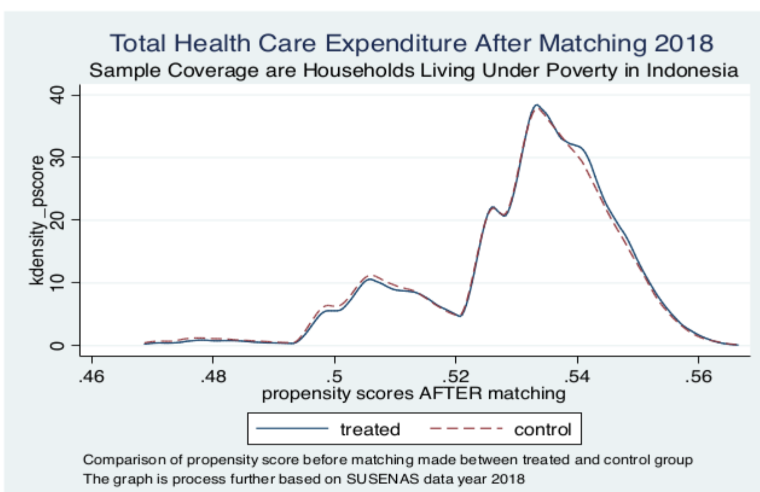
After reached the balancing property for each sample group, we continued the PSM stage process. According to Ho et al. 2007), apart from low R^2, we could continue the PSM method stages if the balancing property was satisfied. This condition was mainly known as propensity tautology. The third step was to check the reduction bias of matching results. The six health expenditure variables were the leading variables to be tested. From the results, after matching results, all had reduction bias except for *Prevent* variable; all have p-values at least below 0.05. While based on bias reductions, all health expenditure variables had positive value except for the *Prevent* and *Tradpract* variables.

Figure 4 Total Health Care Expenditure Density Before Matching Stage Year 2018



Note: Only total health expenditures, among other expenses, are displayed as the representative to show the contrast between treated and control groups.

Figure 5 Total Health Care Expenditure Density After Matching Stage Year 2018



Note: Only total health expenditures, among other expenses, are displayed as the representative to show the contrast between the treated and control groups.)

Based on the results of bias checking, there was a similar trend for the two years of observation, namely for preventive expenditures and traditional practices expenditures that were not fit into the PBI program. This could be seen from either the insignificant p-values or the increased biases. For traditional practice spending, this was plausible because this sector was not included in the scope of PBI financing. Nonetheless, preventive healthcare such as immunization was supposed to be covered in PBI service yet shows unfavourable bias reductions.

Table 3 Bias Reduction After Matching Stage in Pool Dataset 2017-2018

Variable	Sample	Mean Treatment Group	Mean Control Group	%Bias	%Bias Reduction	t-test	p > | t |	V (T)/V(C)
Health	Unmatched	210000	190000	5.4	17.3	9.98	0	1.27*
	Matched	210000	200000	4.5		8.07	0	1.20*
Treatment	Unmatched	38238	40189	-2.8	10.8	-5.15	0	1.01
	Matched	38238	39978	-2.5		-4.56	0	1.02*
Medicine	Unmatched	33653	37305	-5.2	0.8	-9.52	0	0.63*
	Matched	33653	37277	-5.2		-8.59	0	0.48*
Prevent	Unmatched	20084	19595	0.6	21.5	1.03	0.304	0.90*
	Matched	20084	20468	-0.4		-0.78	0.433	0.84*
Hospital	Unmatched	98201	69957	9.9	8.5	18.22	0	1.46*
	Matched	98201	72364	9.1		16.36	0	1.40*
Tradpract	Unmatched	22653	26621	-4.5	-6.8	-8.21	0	0.85*
	Matched	22653	26892	-4.8		-8.6	0	0.81*

Source: data sources are based on SUSENAS 2017 – 2018, with further modification. Methodology used Propensity Score Matching. The table shows pool data set result reduction bias.

The fourth stage was executing the datasets with three types of PSM methods. The three PSM methods are Nearest Neighbour Matching, Kernel Matching, and Radius Matching. As in the previous stage, there were three research time frames. As can be seen in table four, all the results for each category had the same signs with similar values. For example, for the *Health* category in 2017, all of the outputs had negative values with outcomes around 2000.

The negative difference results were found in several categories in the year 2017 and the combined year group. Meanwhile, in 2018 all outcomes or all expenditure terminals comparisons between users and non-users had positive values. Moreover, the positive number in 2018 was higher than the 2017 results. Regarding the outcomes of t-statistics in parentheses, all of them had values above |1.96| except for the preventive category. Robustness character can be interpreted from the same sign and the output value that are not much difference between one method and another (Khandker et al. 2010)

Table 4 Propensity score matching results – estimated average treatment effect on treated (ATT)

Outcome Variable	2017 - 2018			2017			2018		
	Nearest Neighbor Matching ATT	Kernel Based Matching ATT	Radius Matching (Caliper = 0.1) ATT	Nearest Neighbor Matching ATT	Kernel Based Matching ATT	Radius Matching (Caliper = 0.1) ATT	Nearest Neighbor Matching ATT	Kernel Based Matching ATT	Radius Matching (Caliper = 0.1) ATT
Health	19368.7	19581.5	19166.7	-1875.8	-2669.7	-2655.6	22284.9	14633.7	13987.56
	(9.99)	(10.16)	(9.96)	(-2.43)	(-3.6)	(-3.59)	(6.11)	(4.18)	(4.00)
Treatment	-1796.6	-1921.9	-1951.7	-2987.1	-3968.8	-3929.7	38.3	-1201.3	-1245.5
	(-4.71)	(-5.06)	(-5.15)	(-6.85)	(-9.43)	(-9.37)	(0.06)	(-1.94)	(-2.02)
Medicine	-3604.7	-3547.03	-3651.8	-3346.05	-3328.6	-3302.9	-2966.9	-4030.06	-4124.4
	(-9.4)	(-9.27)	(-9.56)	(-9.81)	(-10.19)	(-10.14)	(-4.36)	(-6.09)	(-6.24)
Preventive	403.3	526.7	489.6	375.03	456.7	415.5	-4191.05	-4385.2	-4504.9
	(0.84)	(1.11)	(1.03)	(1.93)	(2.45)	(2.24)	(-4.59)	(-4.94)	(887.8)
Hospital	28416.9	28548.9	28248.02	7216.95	7445.1	7375.1	37381.5	33056.5	32674.7
	(18.16)	(18.33)	(18.16)	(14.97)	(16.03)	(15.92)	(12.49)	(11.54)	(11.41)
Tradpract	-4050.3	-4025.1	-3967.8	-3134.6	-3274.1	-3213.6	-7976.9	-8806.2	-8812.3
	(-8.31)	(-8.33)	(-8.22)	(-9.81)	(-10.72)	(-10.56)	(-8.97)	(860.02)	(-10.26)

Source: Calculations based on Propensity Score Matching Methods, data sources are based on SUSENAS 2018. ATT is Average Treatment Effects on the Treated. Standard Error are in parentheses. The outcomes show different numerical value in Indonesian Rupiah Currency.

Conclusion

Our research examined the effectiveness of the PBI program in Indonesia from 2017 to 2018. At that time, PBI was a sub-program of UHC in Indonesia. During the implementation, Indonesia's UHC experienced deficits for several years, causing the potential ineffectiveness of the PBI program. Using the PSM method, we tested the implementation effectiveness of the PBI policy. Aligned with the initial hypothesis, we found that the total cash expenditure of PBI users were more significant than non-PBI users. The evidence showed the program's ineffectiveness since PBI had a cashless financing insurance scheme. Therefore, under the PBI program, the out-of-pocket expenditure of the beneficiaries should be lower than non-beneficiaries. Surprisingly, PBI was proven to be effective in certain health expenditure groups. For medicine, health treatment, and traditional practitioners, PBI participants' cash health expenditures were lower in 2017.

To sum up, the PBI program has not effectively reduced health expenditures for the Indonesian poor of various types of health expenditures and periods. From the results obtained, household expenditures were effectively suppressed for spending covered in the initial inspection stage. However, glancing on the health expenses effectiveness outcomes, further health treatment referrals, such as to hospitals and preventive health services, have been ineffective.

Several policy implications were formulated based on our findings. The first was to improve the hospital service system for PBI beneficiaries. Second, in the short term, PBI may ensure the provision of essential vaccinations so that people are more protected from severe diseases that require hospital access. The third was PBI collaboration to expand current health services with other health service channels to spread health awareness and facilities accessibility for the poor. The fourth was to focus on child health programs. This is due to the population of poor children being more than the middle children population. Related to the technical aspect, we suggested that further research can evaluate the PBI program's effectiveness with more sample years. In addition, impact evaluation methods other than PSM can be used as a measurement variation. The pandemic factor, and the elimination of the insurance tier on the effectiveness of PBI can also be considered for further research.

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