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Subsidized health insurance impact among the poor: Evidence on out-of-pocket health expenditures in Indonesia

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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 most extensive UHC program in the world. Under JKN, the poor get free health services through 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 with similar socio-economic characteristics who used PBI and those who did not. We incorporated secondary data from National Socio-economic Survey (SUSENAS). The dataset was executed by using Propensity Score Matching (PSM) methodology. We used health expenditures and socio-economic parameters such as income, education, and gender from the 2017 and 2018 SUSENAS data. We found that in 2017, the total health expenditures of the PBI beneficiaries were lower than the non-beneficiaries. Nevertheless, by merging all two years' data, similar to 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 in which PBI beneficiaries had lower expenses than non-beneficiaries in 2017. Therefore, Therefore, the UHC subsidy program for the poor in Indonesia has not only been ineffective through the years of implementation but also has not been effectively implemented 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 financial difficulties and to reduce direct payments from households at the time of health services use. UHC is one of the realizations of Millennium Development Goals (Onokerhoraye, 2016). The study showed UHC brought hope to improve welfare of the poor (Yilma et al., 2015; Korenman et al., 2016; Ridha & Perdana, 2015; Lu et al., 2020). Nevertheless, the application still faces many challenges (Tinasti, 2015; Yang, 2018), especially for vulnerable populations (Vilcu, 2016).

Pro-poor health insurance can be one of the most effective ways to eradicate poverty (Korenman et al., 2016). In Indonesia, a particular program was allocated for low-income people named Contribution Assistance Recipients (*Penerima Bantuan Iuran* - PBI) was regulated in Indonesia Health Ministry Policy number 28 year 2014. 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 impoverished people 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 (Camacho & Conover, 2013).

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 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.

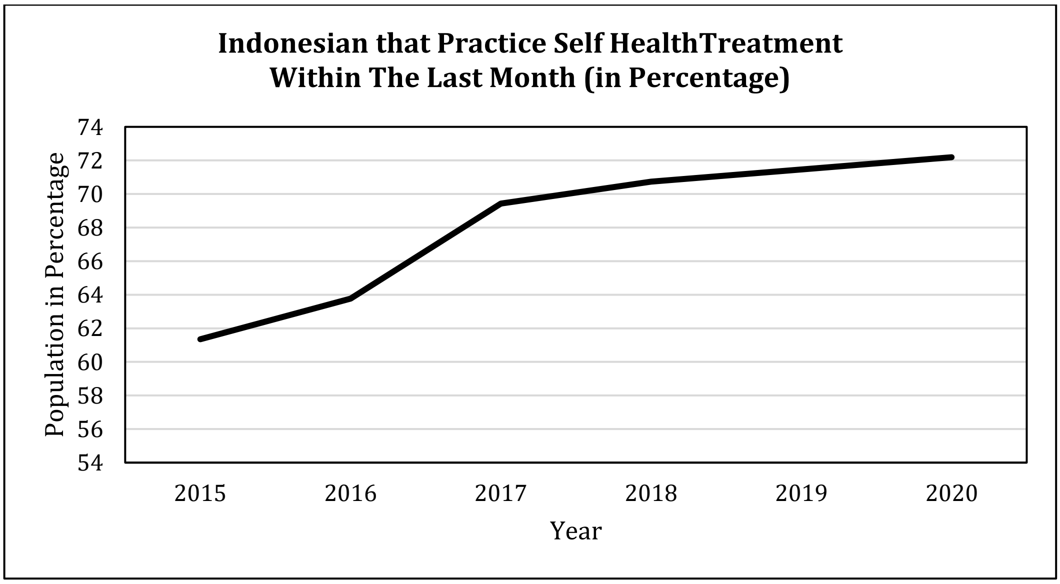

Figure 1 The population that Practice Self Health Treatment Within the Last Month
Source: Indonesia Statistics database. Date Accessed: January 31, 2021.

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 healthcare 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), or catastrophic insurance expenditures for the general population (Situmeang & Hidayat 2018). The results of health insurance world studies were various if we see them from welfare point of view. 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 prices. People would be less inclined to have insurance if there was an increase in premiums for both private and public insurance (Guy et al. 2012).

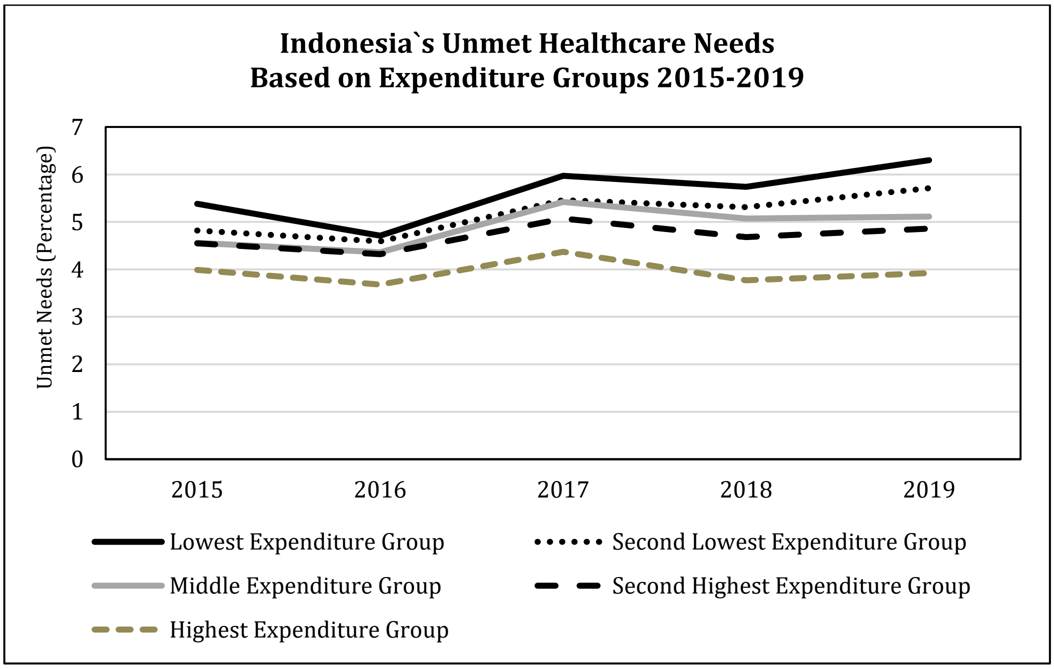

Figure 2 Indonesia's Unmet Healthcare Needs According to Expenditure Group
Source: Indonesia Statistics database. Date Accessed: January 31, 2021.

Our research can fill in the gap from previous works of literature by providing several actions. Firstly, this research examined the effectiveness of the most updated health care subsidized program in Indonesia (PBI) which is still rare up to today in kinds of literature. Secondly, unlike other Indonesia subsidized insurance literature, instead of investigating the general outcome from all the observation years, here we examined each single year's outcome to gain detailed results. 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 detailed examination on health expense classifications instead of only examining one general health expenditure behavior. This expenditure classification approach can 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 Socio-economic Survey (*Survey Sosial dan Ekonomi Nasional* - SUSENAS) years 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 no longer occurred under PBI. While the general results after merging the data for the year 2017 - 2018 showed similar results, with 2018 outcomes, where only certain types of health expenses are effectively reduced under PBI. Where only certain types of health expenses are effectively reduced under PBI. Based on our findings, we suggested that the implementation of PBI must be adjusted actively along with the ascending trend of health costs. PBI coverage may also need 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 behavior can benefit the upcoming related policies and research.

Research Method

For this study, we used *SUSENAS* data years 2018 and 2017. For the pooled dataset, we incorporated 134.493 data. While for the year 2017, 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). For this research, we also used relatively large number of samples as in Sentenac et al. (2016).

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. In the models below, i represents the observation or person, while y represents the year of observations.

$$Health_{iy} = \alpha_1\ Gender_{iy} + \beta_1\ Read_{iy} + \delta_1\ Educ_{iy} + \lambda_1\ Kapita_{iy} \quad (1)$$

$$Medicine_{iy} = \alpha_2\ Gender_{iy} + \beta_2\ Read_{iy} + \delta_2\ Educ_{iy} + \lambda_2\ Kapita_{iy} \quad (2)$$

$$Treatment_{iy} = \alpha_3\ Gender_{iy} + \beta_3\ Read_{iy} + \delta_3\ Educ_{iy} + \lambda_3\ Kapita_{iy} \quad (3)$$

$$Preventive_{iy} = \alpha_3\ Gender_{iy} + \beta_3\ Read_{iy} + \delta_3\ Educ_{iy} + \lambda_3\ Kapita_{iy} \quad (4)$$

$$Hospital_{iy} = \alpha_4\ Gender_{iy} + \beta_4\ Read_{iy} + \delta_4\ Educ_{iy} + \lambda_4\ Kapita_{iy} \quad (5)$$

$$Tradpract_{iy} = \alpha_5\ Gender_{iy} + \beta_5\ Read_{iy} + \delta_5\ Educ_{iy} + \lambda_5\ Kapita_{iy} \quad (6)$$

In the beginning phase of the PSM method logit model needs to be run (Abadie & Imbens, 2016; Keller & Tipton, 2016; Rickles & Seltzer, 2014; Sentenac et al., 2016). In this paper, the logit models used are based on equations one to six, but we changed each dependent variable with PBI variable. The dependent variable in this case is dichotomous. In this case, one means the individual received PBI, while zero means the inverse condition. To observe the dynamics of the spending behavior, we specifically divided the model used into two separate years in purpose to be able to lessen the noise of socio-economic differences and to find more similar characteristics matching observations in the same year. In order 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 many as possible of the samples to get results that were close to the natural condition.

As shown in the descriptive statistics Table 1, there were only two variables representing categorical data, which were Gender and Education. The other variables use numerical data: Educ, Treatment, Medicine, Hospital, and Tradpract*.* From Table 1, *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 decreased from 2017 to 2018. The income per month average value was also increased by IDR 20.120. From Table 1, total 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 is depicted in Figure 3. 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 of 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. Three types of PSM methods were used in this paper, which were Nearest Neighbour Matching, Kernel Matching, and Radius Matching. We also checked the reduction bias after the matching process to check the quality of bias level. The three different PSM were used to gain comparative research outcomes that provided robustness analysis (Khandker et al. 2010).

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 expenditures 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 socio-economic conditions that were related to the health care out-of-pocket expenses. Based on our statistical observation, SUSENAS database were the best to reach the balancing property needed for conducting Propensity Score Matching.

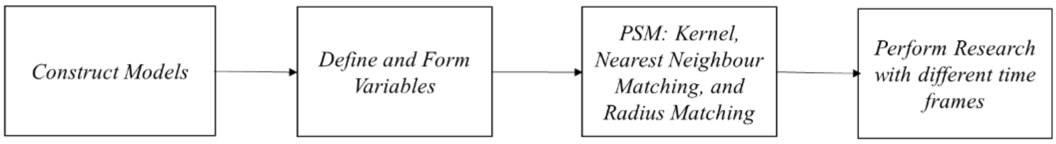

Figure 3 Research Stages

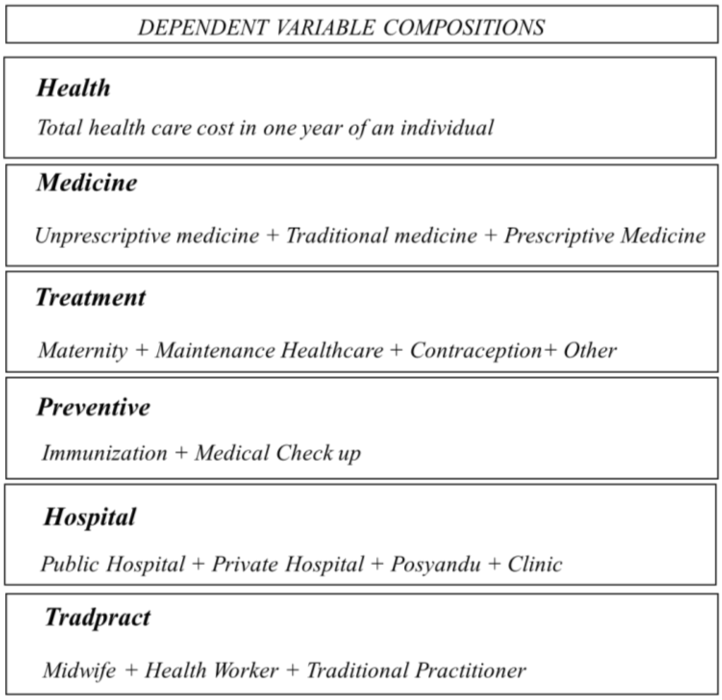

Figure 4 Health Expenditures Variables Composition Based on SUSENAS 2017 and 2018

Figure 4 shows the details of each dependent variable composition. For Health variable, it represents the total out of pocket health expenditures made by the individual for one year. Meanwhile, the Medicine variable was constructed by summed up the out-of-pocket expenditure of non-prescriptive medicine, traditional medicine and prescriptive medicine made by the poor. The research steps we made were explained in Figure 3. In the beginning we constructed the model based on the literature review, then we defined and formed the variables. After that, we performed PSM methods while also checking the model's validity and robustness indicators (Abadie & Imbens, 2016; Keller & Tipton, 2016; Rickles & Seltzer, 2014; Pugo Sambodo, 2018).

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 2017 and 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 2, 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 tendency 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 tended 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 calculated three times scores according to the time frame sample division as in the beginning. We also did a balancing property check while making 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	-0.008	0.005	-0.029**
	(0.011)	(0.015)	(0.015)
Read	-0.026	-0.114**	0.101***
	(0.029)	(0.047)	(0.035)
Educ	-0.049***	-0.058***	-0.036***
	(0.003)	(0.005)	(0.005)
Kapita	-0.00000062***	-0.00000157***	-0.000000536***
	(0.000)	(0.000)	(0.000)
Constant	0.668***	0.948***	0.566***
	(0.057)	(0.081)	(0.071)
Number of obs	134,493	68,809	76,318
LR $chi^2(4)$	198.97	242.96	74.23
Prob > chi^2	0.000	0.000	0.000
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

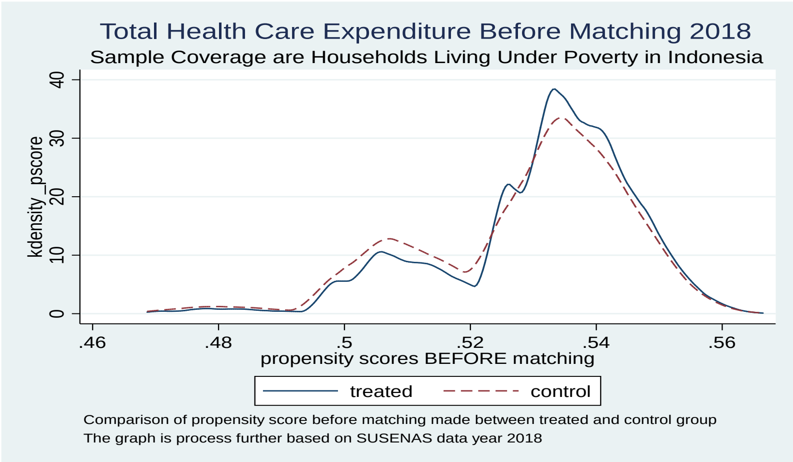

Figure 5 Total Health Care Expenditure Density Before Matching Stage Year 2018
Note: Only total health expenditures, among other expenses, are displayed as the representative to show the contrast between treated and control groups.

After reaching 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. In Figure 5 and 6, we can see the comparison of kernel density results before and after the matching process. The figures show that after matching process, the samples were more similarly distributed.

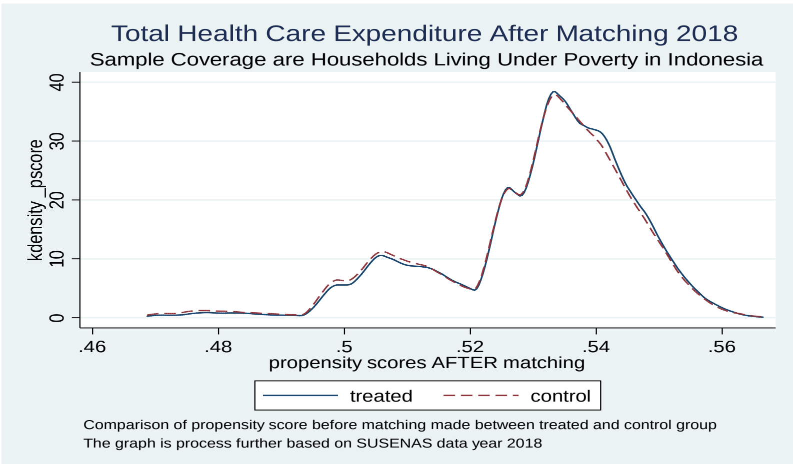

Figure 6 Total Health Care Expenditure Density After Matching Stage Year 2018
Note: Only total health expenditures, among other expenses, are displayed as the representative to show the contrast between the treated and control group.

Table 3 Propensity score matching results – estimated average treatment effect on treated (ATT)

	2017 - 2018			2017			2018		
Outcome Variable	Nearest Neighbor Matching	Kernel Based Matching	Radius Matching	Nearest Neighbor Matching	Kernel Based Matching	Radius Matching	Nearest Neighbor Matching	Kernel Based Matching	Radius Matching
	ATT	ATT	(Caliper = 0.1)	ATT	ATT	(Caliper = 0.1)	ATT	ATT	(Caliper = 0.1)
			ATT			ATT			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. T-Statistics are in parentheses. The outcomes show different numerical values in Indonesian Rupiah Currency (IDR).

Table 4 Bias Reduction After Matching Stage in Pool Dataset 2017-2018

Variable	Sample	Mean		%Bias	%Bias Reduction	t-test	p > | t |	V (T)/V(C)
		Treatment Group	Control Group					
Health	Unmatched	210000	190000	5.4	17.3	9.98	0.00	1.27*
	Matched	210000	200000	4.5		8.07	0.00	1.20*
Treatment	Unmatched	38238	40189	-2.8	10.8	-5.15	0.00	1.01
	Matched	38238	39978	-2.5		-4.56	0.00	1.02*
Medicine	Unmatched	33653	37305	-5.2	0.8	-9.52	0.00	0.63*
	Matched	33653	37277	-5.2		-8.59	0.00	0.48*
Prevent	Unmatched	20084	19595	0.6	21.5	1.03	0.30	0.90*
	Matched	20084	20468	-0.4		-0.78	0.43	0.84*
Hospital	Unmatched	98201	69957	9.9	8.5	18.22	0.00	1.46*
	Matched	98201	72364	9.1		16.36	0.00	1.40*
Tradpract	Unmatched	22653	26621	-4.5	-6.8	-8.21	0.00	0.85*
	Matched	22653	26892	-4.8		-8.6	0.00	0.81*

Source: data sources are based on SUSENAS 2017 – 2018, with further modification. Methodology used Propensity Score Matching. The Table 3 shows pool data set result reduction bias.

The next 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 3, all the results for each category had similar values. For example, for the *Health* category in 2017, all of the outputs had negative values with outcomes around IDR 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 results in 2017. Regarding the outcomes of t-statistics in parentheses, all 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 different between one method and another (Khandker et al. 2010).

Based on the results of bias checking in Table 4, 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 unfavorable bias reductions.

According to Jigjidsuren (2016), the improvement of health insurance for the poor needs political power and multi sectoral movements, while in Indonesia Jung (2016) argued those aspects were necessary but needed more people power for the case in Indonesia.

Technical aspects for making cost cap (Kendall et al., 2019), or improving hospital competitiveness (Sepehri, 2014), could bring health insurance effectiveness came true. Nevertheless, developing countries' implementation needs to learn more from other developing countries rather than developed countries to gain more objective outcomes (Camacho & Conover, 2013).

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.

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 was more significant than non-PBI users. Based on Indonesia's health ministry policy number 28 year 2014, every people living under poverty has rights to get health facilities without paying the insurance cost. Nevertheless, based on our findings, many of the poor still spent out of pocket expenses to cover their health needs, which showed the disparity between society's demand and government policy. 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. PBI participants' cash health expenditures were lower in 2017 for medicine, health treatment, and traditional practitioners.

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

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