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ABSTRACT

Targeting Poverty under Complementarities: Evidence from Indonesia's Unified Targeting System*

Combining nationally representative administrative and survey data with official proxy means testing models and coefficients, we evaluate Indonesia's three largest social programs. The setting for our evaluation is the launch of Indonesia's Unified Targeting system, an innovation developed to reduce targeting errors and increase program complementarities. Introducing a new method of evaluation under the condition of multiple programs, we show that households receiving all three programs are at least 30 percentage points better off than those receiving none. Importantly, the bias from failing to account for program complementarities is greater in magnitude than the benefits of receiving a single program.

JEL Classification: D04, I32, I38, O12

Keywords: poverty, targeting, Indonesia, complementarities

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Introduction

"I can live for two months on a good compliment"

Mark Twain

Targeted poverty programs represent important interventions to reduce poverty in developing countries. Delivering and evaluating these programs are challenging however, specifically with regards to accurately differentiating between poor and non-poor households. Indonesia has a long history of targeted social programs, and since 2005, the Indonesian government has experimented with several methods to identify and access vulnerable groups. These include geographical targeting, community-based targeting and proxy-means testing (World Bank 2012a). Studies by Alatas, et al. (2012) and Cameron and Shah (2014) however, show that a significant proportion of poor households do not benefit from targeted poverty programs in Indonesia.

To address these concerns, the Government of Indonesia (GoI) developed a Unified Targeting System (UDB), called the *Basis Data Terpadu* or Unified Database, through the establishment of TNP2K[1] under the auspices of the Office of the Vice-President of Indonesia and the Indonesian Central Bureau of Statistics (BPS). The unified targeting system approach is typically used to deliver social assistance programs in OECD countries (Grosh et al. 2008), but is rarely implemented in developing countries due to a lack of (complete) information on household welfare.[2] The primary objectives of the UDB are to reduce targeting errors and to increase the complementarities between various poverty programs, by ensuring that poor households receive complementary benefits from multiple programs (TNP2K 2015). The GoI allocates a significant portion of its fiscal expenditure (about 11.5% of total expenditure in 2016), towards social programs. The three flagship social programs are: Health Insurance for the Poor (*Asuransi Kesehatan untuk Keluarga Miskin*, or *Askeskin*, later renamed *Jamkesmas*), Rice for the Poor (*Beras Miskin*, or *Raskin*) and Unconditional Cash Transfers (*Bantuan Langsung Tunai*, or BLT, later renamed BLSM).[3]

[1] *Tim Nasional Percepatan Penanggulangan Kemiskinan* or the National Team for Accelerating Poverty Reduction.

[2] Examples of the use of the unified database for targeting social protection programs in developing countries include the *Cadastro Unico* program in Brazil (De la Brière and Lindert 2005) and the SISBEN System in Columbia (Castaneda and Fernandez 2005).

[3] We are unable to evaluate Indonesia's smaller social programs such as scholarship for the poor (*Bantuan Siswa Miskin*, or BSM), the Conditional Cash Transfer program (*Program Keluarga Harapan*, or PKH) and

Although previous studies have evaluated Indonesia's targeting system they have some drawbacks. For example, studies using field experiments (Alatas et al. 2012; Alatas, et al. 2016) are restricted to small samples across a few villages. This limits their ability to produce externally valid results. Second, previous research has only been able to evaluate single programs. For example, Sparrow (2008) and Sparrow et al. (2013) study the *Askeskin* and *Jamkesmas* programs; Sumarto et al. (2003) and Olken (2005) study the *Raskin* program; and Alatas et al. (2016) evaluate the Conditional Cash Transfer Program. Evaluating programs in isolation may lead to upward biases since individuals' outcomes might otherwise be driven by omitted programs. We address both these concerns.

More specifically, in this paper, we evaluate the impact of the introduction of Indonesia's Unified Targeting System on the targeting and delivery of Indonesia's three largest social programs. We contribute to the literature on poverty targeting through introducing a new method of evaluating poverty targeting under the condition of multiple concurrent programs that *a priori* are expected to complement one another. We subsequently test our method using nationally representative data in conjunction with the official Proxy Means Test (PMT) coefficients and models, thereby exploiting the design of the poverty program. This approach has been argued to be first best when analysing social programs that target poverty (Ravallion 2007). Understanding these complementarities is important since interventions nearly always occur alongside with one another (Grosh et al. 2008); and multifaceted programs for 'ultra-poor' households may have a significantly positive and persistent impact on their chances of exiting poverty (Banerjee, et al. 2015b).

We show that the introduction of the UDB significantly increased the successful targeting of social programs in Indonesia. The probability of targeted households receiving all three programs increased by 117% compared to previous targeting efforts. Households receiving all three programs, experienced an increase in household expenditure of 30 percentage points compared to those that received no programs, and increases of between 16 and 19 percentage points compared to households that received only one or two programs. In other words, our results show that conventional poverty targeting performance evaluations are biased upwards, since they omit the impacts of complimentary programs. Taken together our results justify the implementation of the UDB to improve program targeting and program complementarities between social programs.

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community block grants for education and development (Widianto 2013), since their coverage is not nationwide and in the case of the BSM, beneficaries are nominiated by their teachers.

The rest of the paper is organised as follows. We discuss the evolution of Indonesia's social protection programs and the introduction of the Unified Targeting System in Section 2. In Section 3, we outline our approach to evaluate Targeting Under Complementarities. We then describe the datasets used in the analysis. In Section 4, we evaluate the introduction of the Unified Targeting System on the targeting performance of Indonesia's three most important social programs. Section 5 presents an evaluation of the impact of different program combinations on household per capita expenditure and poverty, thereby highlighting the important role of program complementarities. Finally, the conclusions are presented in Section 6.

B*ackground*

History of Indonesian Poverty Programs

The definition of the poverty line in Indonesia has evolved several times, since its introduction in 1975 (see Priebe 2014). Nevertheless, the majority of the Indonesian population hovers around the national poverty threshold (World Bank 2012a) with approximately half the population living below IDR15,000 per day (around PPP USD 2.25 a day). Marginal shocks therefore have profound effects on household welfare in Indonesia (Pritchett et al. 2000, and Suryahadi et al. 2003). This has made poverty and vulnerability central policy issues for successive Governments.

The GoI introduced social security programs for the first time in 1997 to mitigate the adverse economic and social impact of the Asian Financial Crisis (Daly and Fane 2002; Bacon and Kojima 2006; Grosh et al. 2008; Sumarto and Bazzi 2011).[4] These, the first generation of Indonesia's social protection programs, called *Jaring Pengaman Sosial* (JPS), were implemented under President Habibie's Administration in 1999/2000 (Widjaja 2012). The JPS sought to protect chronically poor households from falling further into poverty while eliminating vulnerable households' exposure to risk (Sumarto et al. 2002). The JPS was tasked with: (i) ensuring the availability of affordable food through the OPK (for *Operasi Pasar Khusus* or Special Market Operation program); (ii) improving household purchasing power through employment creation; (iii) preserving access to critical social services, particularly health through the *Askeskin* (for *Asuransi Kesehatan Penduduk Miskin* or health

[4] Please refer to Figure A1 in the Appendix, which summarizes the evolution of social safety net in Indonesia from 1997 to 2008.

insurance for the poor program), education through the BOS (for *Bantuan Operasional Sekolah* or school block grant program); and (iv) sustaining the local economy through regional block grants and the extension of small-scale credit.[5] In 2002, the GoI changed the OPK to become one of the largest social protection programs named *Raskin* (*Beras untuk Keluarga Miskin* or Rice for the Poor), which aimed to reduce household spending on food, especially on rice.

The second generation of social protection programs were implemented between 2005 and 2008 to alleviate the financial burden on households from rising oil prices (Bacon and Kojima 2006). To mitigate the negative effects, especially on poor and near-poor households, the GoI launched the Fuel Subsidy Reduction Compensation Program, namely *Program Kompensasi Pengurangan Subsidi Bahan Bakar Minyak* (PKPS-BBM) (World Bank 2006, Yusuf and Resosudarmo 2008 and Rosfadhila et al. 2011). Under this scheme, an Unconditional Cash Transfer program was introduced to complement the BLT (for *Bantuan Likuiditas Tunai* or Direct Cash Assistance). This program was subsequently renamed BLSM (for *Bantuan Langsung Sementara Masyarakat* or Temporary Unconditional Cash Transfer program) in 2013.[6] From July to September 2005, the GoI through Statistics Indonesia (*Badan Pusat Statistik* or BPS) conducted a census of poor households for the first time, with the aim of implementing the BLT program. The database was also known as PSE05 (*Pendataan Sosial Ekonomi Penduduk* 2005, or Socio-economic Data Collection of the Population).[7]

In 2008, the GoI once again restructured the nationwide programs. At this time the government's three main flagship program were the BLT, *Raskin* and *Jamkesmas* (see figure 1). These three programs target the same beneficiaries, the poor and the near-poor households, or those households that are 20% above the poverty line, covering 22% of total households in 2009. From the perspective of budget disbursement, BLT spending constitutes 40% of total social assistance expenditure, *Raskin* accounts for 34% and Jamkesmas for 13% (Jellema and Noura 2012).

[5] The GoI disbursed IDR3.9 trillion directly to JPS programs out of a total development budget of IDR14.2 trillion, with financial support from international donors including the World Bank and the Asian Development Bank (Sumarto and Bazzi, 2011).

[6] Under this program, the targeted household received cash transfers delivered via post office (Bazzi et al. 2015). The BLT cash benefit was IDR100,000 (roughly US$10) per month to each targeted recipient household and it was increased to IDR150,000 under the BLSM scheme.

[7] The data collection involved community-based nominations combined with other data to identify prospective beneficiary households based on fourteen selected indicators that represented the well-being of poor households, see Hastuti et al. (2006) for further details.

Introduction of the UDB

Due to concerns about the poor performance of the PSE05,[8] in 2008-2009 the GoI updated the list of beneficiaries by including community verification. This updated version, was known as the PPLS08 (*Pendataan Program Lindungan Sosial* 2008, or Data Collection for Targeting Social Protection Programs). As with PSE05, this database was primarily used to identify eligible households for unconditional cash transfers. Due to time constraints however, the problems associated with PPLS08 were similar or worse than those of the PSE05 and errors in targeting continued (Rosfadhila et al. 2011). Some argue that targeting errors catalysed social unrest (Widjaja 2009; Cameron and Shah 2014).

Explanations for the poor performance of targeting mechanisms and the absence of complementarities in the social protection programs over the period 2005 and 2008 include: (1) alternative methods of targeting implemented by each of the poverty programs;[9] (2) biased results from the targeting design;[10] and (3) different notions of poverty between the views of the community or local leader and the central government. This may have led to some of the programs being diverted away from intended beneficiaries (Olken 2005; Alatas et al., 2012). In 2010 the TNP2K was mandated with the task of reducing the prevalence of poverty to 8% by 2014 and was given the responsibility of overseeing the coordination of three clusters of poverty programs: household-based social assistance programs (e.g. *Raskin, Jamkesmas*, BLT), community empowerment programs and programs to expand economic opportunities for low-income households in areas such as micro-credit (Sumarto and Bazzi 2011; Widianto 2013). This team was also responsible for reducing targeting errors through the development of a Unified Targeting System, as well as monitoring and evaluating the implementation of household level targeted poverty programs (World Bank 2012a).

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[8] Previous studies by Hastuti et al. (2006), Widjaja (2009) and World Bank (2012a), assert that the PSE05 and PPLS08 programs suffered from serious problems. They argue that since households who were nominated by sub-village heads were surveyed with the PMT questionnaire, many poor households were excluded.

[9] For example, prior to 2006, the targeting of the *Raskin* and *Jamkesmas* used the list produced by BKKBN, (for *Badan Koordinasi Keluarga Berencana Nasional* or the National Family Planning Coordination Agency) while the targeting for the BLT program was implemented based on PSE05. From 1994 to 2005, the BKKBN produced an indicator and classification of family welfare and the GoI used this measure to deliver the *Raskin* and *Askeski*n programs in 2005. Based on BKKBN classification, family welfare was divided into five categories: pre-welfare families (pre-KS), welfare family 1 (KS1), welfare family 2 (KS2), welfare family 3 (KS3), and welfare family 3 plus (KS3 Plus). It proved unsuitable for allocating Social Protection since its components were inflexible and inappropriate for measuring economic shocks (Sumarto et al. 2003; Sparrow 2008).

[10] For example, in preparing the list of eligible households, many of the households in the pre-list were not visited, and not all questions asked (World Bank 2012a).

To address some of the identified shortcomings, the GoI between, 2011 and 2014, made significant changes to both the targeting mechanism and the service delivery of poverty programs. The UDB was developed to identify the poorest 40% of the population for inclusion in social assistance programs through proxy means testing. The overarching goal of this development was to improve targeting outcomes both through lowering targeting errors and by increasing complementarities between social assistance programs, which failed to occur under the previous targeting regime (TNP2K 2015).

In comparison to the previous targeting system, a number of improvements were introduced, including: (1) an increase in the number of indicators used to measure household welfare (26 as opposed to 14) from the 2011 poverty census, namely PPLS11;[11] (2) greater coverage of households in PPLS11, reaching 40% of the population surveyed or approximately 24 million households; (3) the implementation of a two-stage targeting process in the data collection of PPLS11;[12] and (4) a PMT model to measure targeting thresholds based on 482 district-specific models, as opposed to using a single national threshold (TNP2K 2015). Figure 2 details the development of UDB and the use of the database for selecting poor beneficiaries of the poverty programs.

Following improvements in targeting, in the third quarter of 2013, the GoI also introduced the Social Security Card (*Kartu Perlindungan Social - KPS).* This card, covering almost 25% of the poorest households or 15.5 million poor and vulnerable households from the UDB was aimed to entitle households to *Raskin*, temporary unconditional cash transfer (BLSM) and financial assistance for students of those family members (TNP2K 2015). According to an ad-hoc committee established to diseminate information with regards to oil price subsidy reduction (*Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak* 2013), this card could also be used to access the *Jamkesmas* program. This is reasonable since, as shown in Figure 1, the coverage of *Jamkesmas* is far higher than the coverage of the KPS. To ensure that every eligible household received the card without disruption, the GoI employed the postal mail service and cards were delivered directly to households where possible.

[11] *Pendataan Program Lindungan Sosial 2011*.

[12] The two-stage data collection involves (i) the earlier lists of households using data from PPLS08 and Population Census in 2010 are compiled through poverty mapping; the (ii) it was complemented with the results of consultations with low-income groups and through impromptu discussions and general observations (Bah et al. 2014)

Targeting Under Complementarities

The most popular indicators to measure targeting performance are leakage and undercoverage. Under conditions of perfect targeting, transfer programs are only directed to those individuals/households that are genuinely poor (as defined by a set criteria). There is potential however, for two types of targeting errors, namely Type I errors (*undercoverage*) and Type II errors (*leakage*) (see Coady, Grosh, and Hoddinott 2004 for more details). These standard measures have been criticized and several extended targeting performance measures have been developed. For example, Galaso and Ravallion (2005) introduce a single index called the Targeting Differential (TD), which measures the difference between the proportion of the poor and the non-poor who become program beneficiaries. Coady, Grosh, and Hoddinott (2004) construct the CGH index, which measures the proportion of the transfer budget received by a population quantile divided by the portion of the population in that quantile. The World Bank (2012b) proposes the normalized CGH also known as the targeting gain, which evaluates the extent to which the current program deviates from a perfect setting. An important feature of all these performance measures is that they can only evaluate the targeting performance of a single poverty program. If we wish to evaluate the targeting performance of multiple programs simultaneously, we need to adopt an alternative approach, particularly since programs are likely to compliment one another. As shown in Table 1, errors of inclusion and exclusion can be redefined under conditions of complementarity.

To simplify, with no loss of generality, we assume that the beneficiaries of all three programs are poor households. The three programs, BLT, *Raskin*, and *Jamkesmas* are abbreviated using (B), (R), and (J) respectively. Therefore, B_B or B_R or B_J (the total number of beneficiaries in each program) is equal to P (the total number of individuals deemed poor). Similarly, the total number of non-beneficiaries under each program is denoted by NP. The term ee_T refers to the share of the poor households that do not receive any program relative to the total number of poor households (or errors of exclusion), and can formally be written as:

$$ee_T = \frac{E2_B}{P} + \frac{E2_R}{P} + \frac{E2_J}{P} = \frac{E2_B + E2_R + E2_J}{P} \quad (1)$$

The error of inclusion ei_T comprising of the ratio of the non-poor beneficiaries to the total number in each of the programs, and can be written as:

$$ei_T = \frac{E1_B}{B_R} + \frac{E1_R}{B_B} + \frac{E1_J}{B_J} = \frac{E1_B + E1_R + E1_J}{P} \qquad (2)$$

To evaluate poverty targeting under program complementarities, we propose evaluation methods using probabilities that measure the likelihood of a poor household receiving either one, two, or all three programs simultaneously, else no program at all. Table 2 (column 2) shows the joint probabilities of poor households participating in one, two, all three programs, or no program at any given time. The marginal probabilities of poor households receiving each program ares presented in Columns 3-5 of Table 2. Under perfect complementarities, the joint probability of poor households receiving all three programs will be equal to the total marginal probability for all programs. Under this condition, the joint probability for poor households receiving either one or two programs will therefore be zero.

Using the information in Table 2, we further measure the degree of complementarity of each program with respect to the others. For example, the complementarity between BLT and *Raskin* is measured by:

$$P(BLT = 1|Raskin = 1) = \frac{(C_{B=1,R=1,J=0}/P) + (C_{B=1,R=1,J=1}/P)}{C1_B/P} \qquad (3)$$

Where $P(BLT = 1|Raskin = 1)$ denotes the conditional probability of the poor households receiving the BLT, given that they also receive benefits from the *Raskin* program. The term $(C_{B=1,R=1,J=0}/P)$ represents the joint probability of receiving both BLT and *Raskin* programs and the expression $(C_{B=1,R=1,J=1}/P)$ is the joint probability of receiving all three programs. The denominator $C1_B/P$ refers to total marginal probability of receiving the BLT program.

The complementarity of the BLT program with respect to the two other programs can be assessed using:

$$P(BLT = 1|Raskin = 1, Jamkesmas = 1) = \frac{(C_{B=1,R=1,J=1}/P)}{((C_{B=1,R=1,J=1}/P) + (C_{R=1,J=1,B=0}/P))} X\ 100 \quad (4)$$

Where $P(BLT = 1|Raskin = 1, Jamkesmas = 1)$ measures the likelihood of a poor household receiving BLT given that they also participate in the other two programs. The term $(C_{B=1,R=1,J=1}/P)$ represents the joint probability of poor households participating in those three programs, while $(C_{R=1,J=1,B=0}/P)$ is the joint probability of the poor households receiving both *Raskin* and *Jamkesmas* programs.

Data

To evaluate the performance of poverty targeting under the UDB, the analysis draws from the National Socioeconomic Survey (SUSENAS), the Social Protection Survey (SPS) and the Village Potential Census (PODES) described in detail below. Figure 3 provides a time-line of the various data collections. Crucially we use the official PMT coefficients that are unique to all 482 districts of Indonesia in order to estimate each household's PMT score, thereby ensuring as close a comparison as possible with the official PMT used in developing the UDB. The TNP2K team using data from the SUSENAS and PODES surveys, developed PMT models that are unique to each regency and city because a variable affecting household welfare status in one municipality or district may have little significance in others areas (see Bah et al. 2014). Using each district's unique PMT model, we predict household PMT scores and estimate household expenditures as pre-treatment indicators.

SUSENAS Surveys

The National Socioeconomic Survey (SUSENAS) is an annual cross-sectional, nationally representative dataset, initiated in 1963-1964 and fielded once every year or two since then. In 2011, however, the BPS changed the survey frequency to quarterly. This covers some 300,000 individuals and 75,000 households quarterly. In this paper, we utilize data from the 2005, 2009 and 2014 waves of the SUSENAS survey to: (1) measure the benefit incidence from poverty programs and their targeting performance relative to previous efforts; (2) predict the poverty level of each household; and (3) estimate the relationship between poverty, social protection eligibility and household characteristics, particularly using the 2014 SUSENAS survey.

Social Protection Survey (SPS)

The second dataset used in the analysis is the 2014 Social Protection Survey (SPS), which was conducted jointly by the Central Bureau of Statistics of Indonesia (BPS) and the Vice President's National Team for the Acceleration of the Poverty Reduction (TNP2K) as a supplement to the SUSENAS. This survey was implemented from the first quarter of 2013 to the first quarter of 2014, and was specifically aimed at examining the performance of poverty targeting under the implementation of the UDB. A question pertaining to the KPS (for *Kartu Perlindungan Sosial* or the Social Security Card) was only asked in the last two rounds. Therefore, we use data from the first quarter of 2014 since it was the period just after the implementation of the KPS. We use this survey to obtain information about the implementation of KPS related to the benefits received by poor households from the poverty targeting.

Village Census (PODES)

The last source of data is the 2014 PODES, which provides information on all villages/*desa* in Indonesia. This village census covers a sample of around 80,000 villages and is fielded around periodic censuses (Agriculture, Economy, Population). It includes useful information on village characteristics, including the main sources of income, population and labor force characteristics, socio-culture, type of village administration and the other relevant village-level information.

Merging the datasets

Since 2011 the BPS has not published the village and subdistrict code for the SUSENAS dataset, meaning that the process for merging these datasets is challenging. In meeting this challenge, we merge the data as follows:

i) We merge the Quarter 1 2014 SPS with Quarter 1 2014 SUSENAS using the normal household ID that is available in these two datasets. In all we merge 70,336 households of the SPS sample to the total 71,051 sample of the SUSENAS.
ii) We merge those two datasets with the 2014 pooled SUSENAS data to obtain village and sub-district IDs using a 'bridging code' shared privately with us by the BPS.[13]
iii) Finally, we merge the resulting dataset with the PODES data using village ID to obtain village level variables. After merging with the PODES data, we are able to identify 67,118 households as well as details of their expenditure, social protection and village information that can be combined with the official PMT coefficients in order to obtain individual household PMT scores (see below).

All the variables used in this study are presented in Tables A1 and A2 in the Appendix.

[13] We are grateful to a BPS staff member who provided us with this bridging code.

The implementation of the UDB, targeting errors and complementarities

The poor performance of poverty targeting based on the PSE05 is confirmed in the 2005 panel (Table 3), which presents joint and marginal probabilities of receiving different program combinations in that year. The probability of a poor household receiving *Raskin* was 67.8%, significantly higher than the 56.2% for BLT and 21.3% for *Jamkesmas*, respectively. Another striking feature is with regards to program complementarities. For example, as shown in the first column of Table 3, only 15.7% of eligible poor households receive all three programs, while 21.6% received none.

The conditional probabilities of participating households in the 2005 panel are provided in Table 4, which can also be used to measure the complementarity between social assistance programs. For example, the probability of a poor household receiving *Raskin*, given that they are a recipient of both BLT and *Jamkesmas* is higher than 90%, while the probability of a poor household participating in both BLT and *Raskin* to also receive the *Jamksemas* programs is 33.6%.

The results of targeting based on the PPLS08 for the 2009 panels are presented in Tables 3 and 4 respectively. The joint probability of poor households receiving three programs based on the PPLS08 targeting method is slightly lower than targeting based on PSE05 (12.7% as opposed to 15.7%). Table 4 shows that in 2009 the complementarities of the three programs were almost identical, albeit a little worse, to the previous targeting regime. For example, among poor households that were *Raskin* recipients, only 57.9% received BLT transfers and 25% received benefits from the *Jamkesmas* program, respectively.

The performance of poverty targeting after the introduction of the UDB is significantly better than the targeting based on the PSE05 and PPLS08, as illustrated in the 2014 panels of Tables 3 and 4. This may be due to some improvements in data collection, superior coverage and the development of the PMT. With regards to marginal probabilities, there was no significant improvement in *Raskin* and BLT beneficiaries from poor households compared to previous targeting efforts. *Jamkesmas* participation however more than doubled. Importantly, the joint probability of participation in all three programs more than doubled between 2009 and 2014, from 12.7% to 27.5%; while the proportion of poor households that did not receive any program decreased from 27.6% to 17.6% over the same period.

As shown in Table 4, program complementarities dramatically improved following the introduction of the UDB. Among poor households who benefited from the BLT for example, 75.2% were also *Raskin* recipients, while 72.8% also received *Jamkesmas* benefits. These figures are significantly higher than the unconditional probability of receiving *Raskin* (65.8%) and *Jamkesmas* (49.4%). In 2014, 72.3% of *Jamkesmas* beneficiaries from poor households also received BLT and 74.3% also received *Raskin*.

This evidence provides the first indication that there was an improvement in the program complementarities between the three poverty programs, even though only 49.1%, 65.8%, and 49.4% of poor households received benefits from the BLT, *Raskin*, and *Jamkesmas* program, respectively. These findings mean that for the BLT and *Jamkesmas* programs, more than 50% of the targeted households were still erroneously excluded from receiving the benefits from those programs.

Did the KPS improve poverty targeting and Poverty Programs complementarities?

While our previous analysis highlights the improvements made in poverty targeting and program complementarities following the introduction of the UDB, in this section we further examine the impact of the introduction of the KPS on these outcomes. The KPS (which covered the bottom quartile of the population) was introduced as a means of confirming the eligibility status of beneficiaries while also providing information about social programs.

Table 5 compares the joint and marginal probabilities of participating in the poverty programs comparing poor households that received the KPS (KPS holders) to those that did not (Non-KPS holders). From columns (5) and (9) we observe that the joint probability of participating in all three programs for KPS holders is significantly higher than for non-KPS holders (56.8% as opposed to 3.8%). Conversely, the joint probability of not receiving any of the three programs for a KPS holder is significantly lower than for a non-KPS holder (0.4% compared to 31.4%). The marginal probabilities are also much higher for KPS holders. For example, the probability of receiving BLT is 96.3% for KPS holders, while it is only 11% for non-KPS holders.

Table 6 demonstrates that the introduction of the KPS also improves the complementarities between poverty programs. Among KPS holders, for example, the likelihood of receiving BLT for those who also received *Raskin* and *Jamkesmas* is much higher than for Non-KPS holders, (97.5% as compared with 19.8%). Similarly, the probability of KPS holders to receive *Jamkesmas*, while also being BLT and *Raskin* beneficiaries is 77.4%, while it is only 1.6% for non-KPS holders.

This evidence complements the findings of Banerjee et. al (2015) in the context of the *Raskin* program since those authors find that eligibility status and information provision significantly increased subsidies received by beneficiaries. While the present study focuses on the extensive margin, we further show that receiving the KPS increases the probability of poor households receiving additional programs.

Empirical Estimation

While the introduction of the UDB and the KPS significantly improved poverty targeting and program complimentarities, it is imperative that we assess the impact of targeting complementarities on household welfare.

We are primarily interested in the average treatment effect on the treated (ATT), θ, of participating in one or more of several poverty programs R, relative to the counterfactual of not receiving one or more of the programs, such that:

$$\theta_{\widetilde{r0}} \equiv \theta_r - \theta_0 \equiv E[Y_h^1(\theta_r) - Y_h^0(\theta_0) \,|R = r] \tag{5}$$

for potential outcomes of household h. Our goal is to identify the parameter vector $\delta \equiv (\theta_{\widetilde{30}}\,; \theta_{\widetilde{20}}\,;\ \theta_{\widetilde{10}})$. We therefore denote the difference in per capita expenditure (PCE) as:

$$(PCE_{h,+1}|R=r)-(PCE_{h,t+1}\ |R=0)= \theta_{\widetilde{r0}}+\varepsilon_{h,t+1} \tag{6}$$

Where $\theta_{\widetilde{r0}} = \theta_r - \theta_0$ is the average-on-the-treated effect and $\varepsilon_{h,t+1}$ is the error term. Since our study relies on observational data, we must ensure that $\varepsilon_{h,t+1}$ is as close to zero as posssible such that our results equate as closely as possible to quasi-experimental.

Taking into consideration the advantages of efficiency and practicality, following Hirano et al. (2003) and Abadie (2005) and Bazzi et al. (2015), we implement a semiparametric reweighting estimator.[14]

[14] Reweighting estimators often have better finite sample properties than common matching procedures (Busso et al. 2014), and given that, multiple treatments are considered, it is computationally less complicated.

Estimation of the Propensity Score

Propensity score estimation, which can be used to adjust for differences in pre-treatment variables, is a crucial step when matching is implemented as an evaluation strategy (Rosenbaum and Rubin 1983, 1984). The underlying principle is that the preintervention variables that are not influenced by participation in the program should be included in the regression (Jalan and Ravallion 2003).

Non-experimental estimators can benefit from exploiting the design of program design for identification.[15] The first-best solution is to estimate the propensity scores using both the PMT score generated from official coefficients used by the GoI as well as the underlying variables selected for the construction of the PMT score.[16,17] The PMT score for the poorest 40% in the UDB was measured using the district-specific models for the 471 Indonesian districts.[18] We apply these official district-specific coefficients, using data from the first quarter of 2014 to generate $\hat{p}_h$, the probability that a household received the poverty program. The second scenario uses the same covariates as used in the PMT model, as detailed in Table A3 of the Appendix.

The results are shown in Figure 4. The estimation of the propensity score based on the PMT scores alone are shown in the left panel (A), while the estimation using the underlying covariates is shown in the right panel (B). The estimation based on the PMT score is demonstrably better in terms of the considerable overlap in the propensity score of treated (T=1) and control (T=0) units. We therefore select the PMT score-based estimates as inverse probability weights to rebalance recipient and non-recipient households along observable dimensions.

[15] We also attempted to merge the SPS data with the UDB database so as to estimate the PMT score for each household. Using KPS codes to facilitate the merge, however, we only managed to match 5,669 households from the SPS sample of 70,336 and the UDB sample of 25.5 million households. Ultimately, the matched households all belonged to the same consumption decile and did not vary sufficiently in terms of their PMT score, number of poverty programs received and household characteristics. These matched data fail to generate a sufficiently large region of common support, or so-called "failure of common support" (Ravallion 2007).

[16] We are grateful to TNP2K for providing us with access both to the PPLS 2011 database and the 471 district-specific coefficients for generating the UDB database.

[17] Most covariates attributed to the non-poor condition of households have a negative relationship with the probability of receiving poverty programs. Those conditions, for example, include (1) the likelihood of male headed households receiving the government programs is lower than compared to the female-headed households; (2) The household head's higher education level has a negative relationship with their probability of receiving the programs; (3) Households who have household's assets (e.g. gas $\geq$ 12 kg[17]; refrigerator; motorcycle) is less likely to receive the poverty programs.

[18] There are 482 districts in Indonesia, of which we use 471 in our analysis since 11 districts are dropped when we merge our data.

Balancing Groups

Next we reweight the sample to ensure that the non-treated group is as comparable as possible to the treated group (in terms of the propensity score). As described by Abadie (2005), Smith and Todd (2005) and Busso et al. (2014), all estimators adjusting for covariates can be understood as different methods to weight the observed outcomes using weight, $\widehat{\omega}$.

We can therefore rewrite the average treatment effect on the treated as:

$$\hat{\theta} = \frac{1}{N_1} \sum_{h=1}^{N} \hat{p}_h \widehat{\omega}_h Y_h - \frac{1}{N_0} \sum_{i=1}^{N} (1 - \hat{p}_h) \widehat{\omega}_h Y_h \qquad (7)$$

$$N_1 = \sum_{h=1}^{N} \hat{p}_h, \qquad N_0 = N - N_1 \qquad (8)$$

Where N represents the sample size of an i.i.d sample, N_1 denotes the size of the treated subsample and $\hat{p}_h$ the sample's predicted probability of receiving any poverty programs.

Following Busso et al. (2014), we normalize the weights such that: $\frac{1}{N_0} \sum_{h=1}^{N} (1 - \hat{p}_h) \widehat{\omega}_h y_h = 1$. The contribution of the non-recipient to the counterfactual, $\widehat{\omega}$, can then be directly computed as proportional to their estimated odds of treatment, $\widehat{\omega_h} = \frac{\hat{p}_h}{1-\hat{p}_h}$.

Figure 5 shows the distribution of the baseline PMT across treatment levels. Reassuringly, households receiving all three programs are on average relatively poor, compared to other households. Conversely, households that do not receive any program benefits (i.e. our control group) are relatively rich when compared to other groups. After reweighting however, the distribution of the control group moves significantly to the left, therefore significantly improving the overlap with the treatment groups.

Alternative Estimators of the Average Treatment Effect

Studies by Imbens and Wooldridge (2009) and Busso et al. (2014) discuss different estimators (beyond OLS) that are suitable under the reweighting approach. Following these, we consider (1) reweighting estimators using the estimated odds of treatment, $\widehat{\omega}$; (2) double robust estimation controlling the IPW estimators using either their propensity scores, ($\hat{P}_h$) or the PMT score (PMT_h), as suggested by Scharfstein et al. (1999) and Lunceford and

Davidian (2004);[19] (3) Control function estimation, following Rosenbaum and Rubin (1984), which stratifies the propensity score into five subclasses. The average treatment effect on the treated is measured within a specific stratum and is then weighted across strata.

Results

Household Per Capita Expenditure

Table 7 presents the estimation of the ATT using as the dependent variable the difference in per capita expenditure (PCE) before and after treatment. This outcome variable is measured using the ratio of real per capita consumption in 2014 and an estimate of real per capita consumption, which is generated using 471 district-specific coefficients of the UDB.[20] Over the period of study, households that did not receive any poverty program experienced a decrease in their PCE of between 19 and 35 percentage points.

Households that received all three programs enjoyed PCE growth of around 33 percentage points on average (Table 7). Similarly, poor households that received two poverty programs also experienced an increase in their PCE, though at a lower rate as when compared to households that received all three. Compared to households that did not receive any programs, households that received two programs enjoyed a rise in per capita expenditure of about 26 percentage points on average. Households that received only one program experienced negative growth in PCE of 13 percentage points on average. Comparing these households to the non-receiving group however, we observe that these households are still better off (by around 15 percentage points) relative to those households that did not receive any program.

Summing up, the implementation of multifaceted poverty programs are shown to significantly impact on per capita expenditures of poor households. A household that received one program experienced a negative growth in PCE. This may be because during the

[19] Under this treatment, the estimation produces consistent estimators, while also potentially reducing bias due to any misspecification of the propensity score.

[20] Steps to measure the variable of pre-treatment real per capita expenditure include: applying the UDB district-specific coefficients to the 2014 database to generate an estimate of per capita household expenditure, adjusting the estimate of per capita household expenditure for CPI inflation during the first quarter of 2011 as to make per capita household expenditure as close as possible to the condition before the treatment implemented in the second and the third quarter of 2011. To investigate whether this estimated real per capita expenditure for each district is comparable with the 2011 real per capita expenditure, we compare them with the real per capita expenditure using data from SUSENAS 2011. The results confirm that there is no significant difference between estimated and real per capita expenditure. This is unsurprising because the PMT coefficient used in the UDB was also developed using data from SUSENAS 2011.

study period, the GoI reduced the fuel price subsidy, which resulted in inflation in the basket of goods used by the poor (World Bank 2006, and Yusuf and Resosudarmo 2008).

Next we estimate the impact of multifaceted poverty programs on the Poverty Gap Index. This index (popularly known as P1) measures the extent to which individuals fall below the poverty line (the poverty gap) as a proportion of the poverty line. The sum of all poverty gaps provides the minimum cost of eliminating poverty if transfers were perfectly targeted. We measure each household's poverty gap as a proportion of their district's poverty line before and after the treatment. The poverty gap prior to the treatment is measured using estimated real per capita expenditure for district- specific models compared to the poverty line of the SUSENAS 2011. The post-treatment gap is measured by comparing real per capita expenditure and the poverty line from the SUSENAS data for the first quarter of 2014.

These findings presented in Table 8 confirm that recipients of the multifaceted program experience a decline in the gap as a proportion of the poverty line. Households that receive three programs (upper panel of Table 8) experience a decrease of around 9 percentage points on average. Concurrently, the poverty gap of the control group increases by almost 2.6 percentage points. Taken together, we observe that on average the poverty gap of those households that receive all three programs shrunk by around 3.5 percentage points.

Similarly, we observe a decrease in the poverty gap for those households that receive two programs, compared to non-receiving households of around 3.2 percentage points. Overall, our evidence confirms that by receiving multifaceted programs, households enjoy both significant increases in their per capita expenditure and reductions in their poverty gap relative to the poverty line.

Bias in Existing Studies

Importantly from Table 9 we observe the inherent bias that exists when evaluating the impact of a single program relative to all three, which is estimated to be between 16 percentage points and 19 percentage points. These estimates are even greater than our estimates of receiving a single program relative to receiving no program at all, casting serious doubt on the findings of many existing studies including: studies using Indonesian data that evaluate the targeting performance of single programs (e.g. Alatas et al. 2012, Sparrow, et al. 2013), papers that evaluate social programs in isolation (such as: Bah, et al. 2014 and World Bank

2012a) as well as comparable programs that have been evaluated elsewhere (see: Coady, Grosh, and Hoddinott 2004).

These doubts likely occur both in terms of upwardly biased estimates on individual outcomes from evaluating single policies, but importantly also in terms of the estimated targeting errors. For example in column 10 of Table 3, 49.1% of poor households receive the BLT program, meaning that that exclusion error in terms of BLT alone is 51.9%. The true targeting error however, is rather equal to 100 minus the marginal probability of receiving all three programs, which is equal to 72.5%.

Finally, in terms of the types of targeting adopted, Alatas et. al.'s (2016) study claims that the self-targeting on PKH[21] beneficiaries is likely to reduce the poverty gap by between 29 and 41 percentage points compared to automatic screening. Our results rather suggest that such comparisons are difficult to make when analysing targeting improvements when considering single programs in isolation.

Does the Type of the Program Matter?

We also examine which type of program delivers the greatest impact on household per capita expenditure, thereby contributing to the debate on cash vs. in-kind transfers and the circumstances in which they apply (see for example: Lindert et al. (2007), Currie and Gahvari (2008), Khera (2014) and Hidrobo et al. (2014). In Table 9 we present the impact on per capita expenditure of receiving each combination of poverty programs relative to every other combination. More specifically, the bottom rows of columns 9-11 show that the impact of receiving a single programs is marginal and statistically insignificant. In the bottom row of column 9 for example, we can see that the impact on household expenditure of receiving either BLT or *Raskin* is statistically insignificant from one another. Even though, in terms of the amount of subsidy, the subsidy received from BLT (cash with amount IDR. 100.000 (or USD 10)) is slightly higher than from *Raskin* (IDR. 80.000 (or USD 8)). Interestingly, if we compare the benefit of receiving two programs, *Raskin* and *Jamkesmas*, there is no differential impact and the coefficients are statistically insignificant. We hypothesise that this may be because the benefits of either *Raskin* or BLT are marginal to the total household expenditure. Moroever, this evidence contradicts previous research by Hidrobo et al. (2014),

[21] PKH is an Unconditional Cash Transfer run by the Ministry of Social Affairs of Indonesia which targets the bottom 5% of the population. PKH beneficiaries receive direct cash transfer ranging from IDR. 600,000 to IDR. 2.2 million or (about USD$67–$250) depending on their family composition, school attendance, pre-/postnatal check-ups, and completed vaccinations.

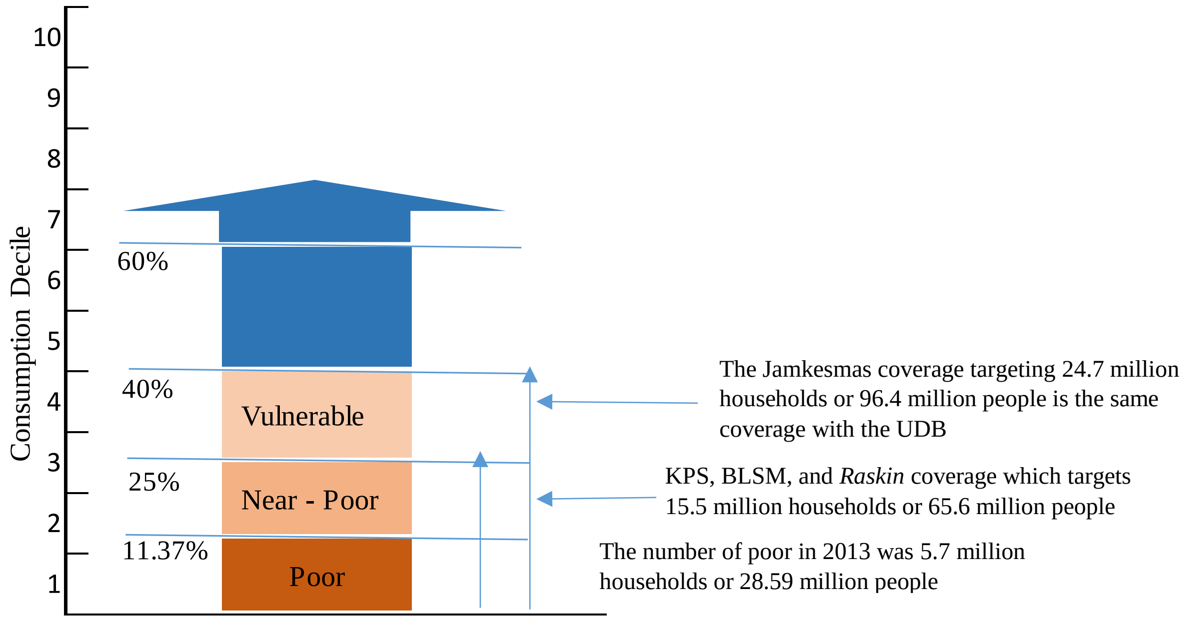
who claim that cash is preferable if the objective of the transfers are to improve household welfare.

Conclusion

Social programs aimed at targeting poverty constitute crucial welfare interventions designed to improve the welfare of poor households. The evaluation of these programs however, have been stymied by the fact that they are evaluated in isolation, which may result in serious upward biases due to individuals' outcomes being primarily driven by omitted programs. In this paper, we combine unique proxy means testing administrative data and survey data from various sources pertaining to the three largest social programs in Indonesia, accounting for more than 80% of total social expenditure, to evaluate the nationwide impact of program complementarities on household expenditure and poverty reduction. Our evaluation takes place before and after the introduction of Indonesia's Unified Targeting system, which was introduced to reduce targeting errors while increasing complementarities between programs. Our results show that the introduction of the Unified Targeting system more than doubled the proportion of households that benefited from all three social programs.

To evaluate the role of complementarities on household expenditure and poverty, we introduce a new method of evaluation. Exploiting the design of all three poverty programs, we then estimate the impact of targeting under the condition of multiple programs and show that households that receive all three programs are at least 30 percentage points better off than those that receive none. We further provide evidence that the level of bias from failing to account for program complementarities, of between 16 and 19 percentage points, is greater in magnitude than the benefits of receiving a single program, thereby demonstrating the clear need to account for program complementarities. Further speaking to the cash vs. in-kind transfer debate, we show in the context of Indonesia that the type of program has no discernible effect on household welfare or poverty.

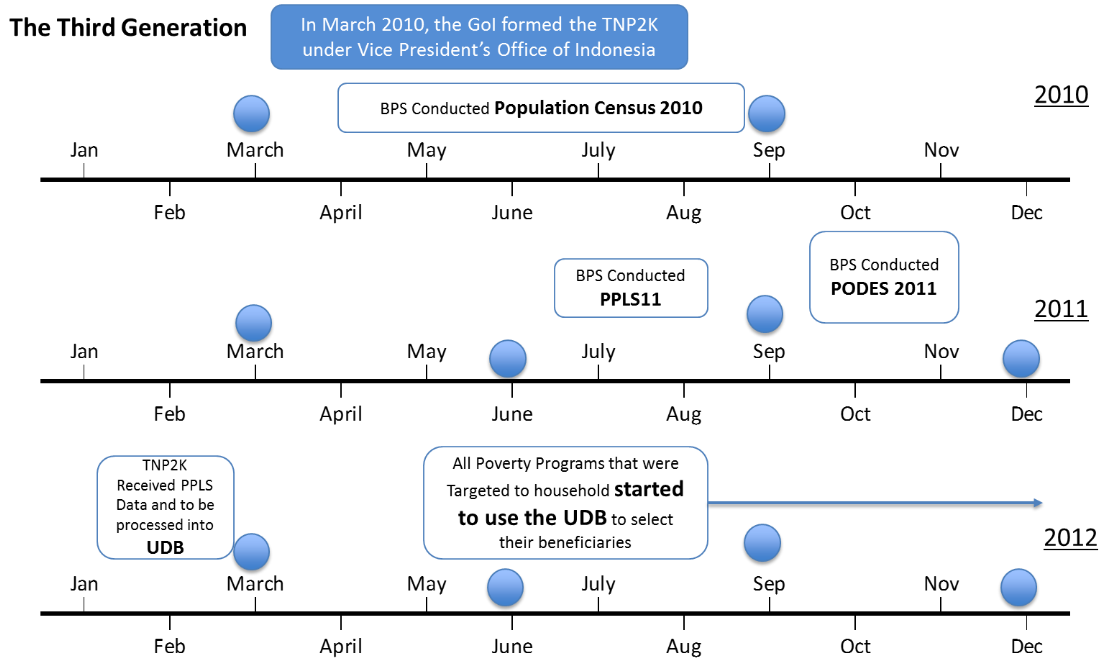
Figure 1. The Coverage of the UDB and Indonesia's Three Largest Poverty Programs



Source: *Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak* (2013)

This figure represents the coverage of the Unified Data and the biggest three poverty programs in Indonesia. For example in 2013, the percentage of the poor household is about 11.37, while the *Raskin* and BLSM covers approximately the bottom 25% of the population which the list of beneficiaries are extracted from the UDB.

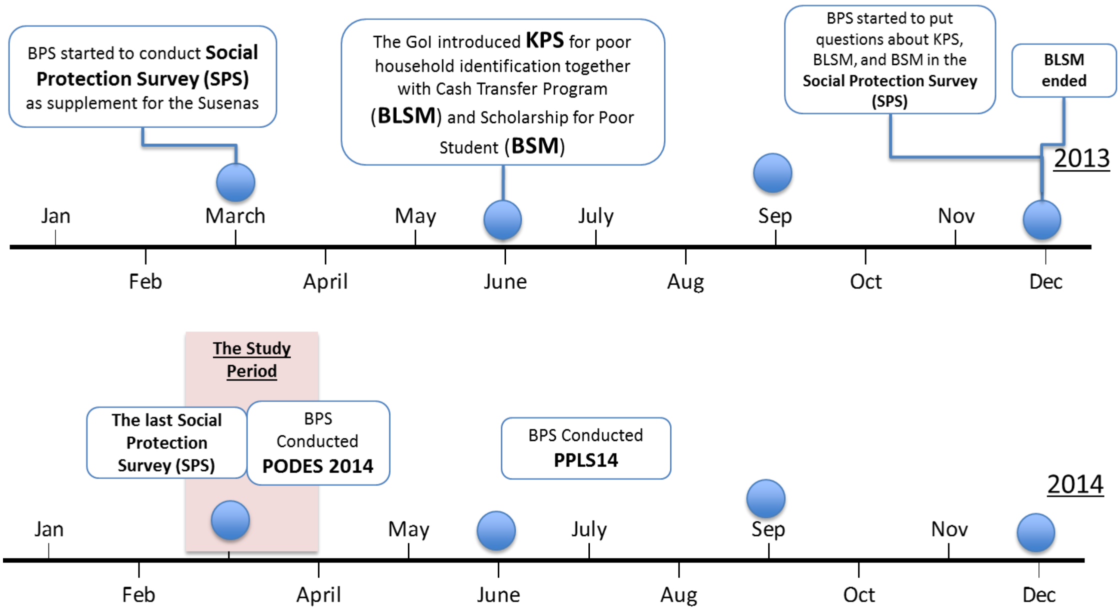
Figure 2. Third Generation of Social Protection Programs and Development of the UDB



This figure presents the time line of the introduction of the third generation of social protection in Indonesia which was started by the development of the UDB in 2012. The list of households in the UDB was constructed using the PPLS 2011 dataset and rank using PMT with 482 unique cut-offs for each district.

Source: Authors' tabulation from multiple sources of the GoI official documents such as the guideline of SUSENAS Survey, Population Census, Podes, and others. Note: the blue dots denote the periods of SUSENAS survey

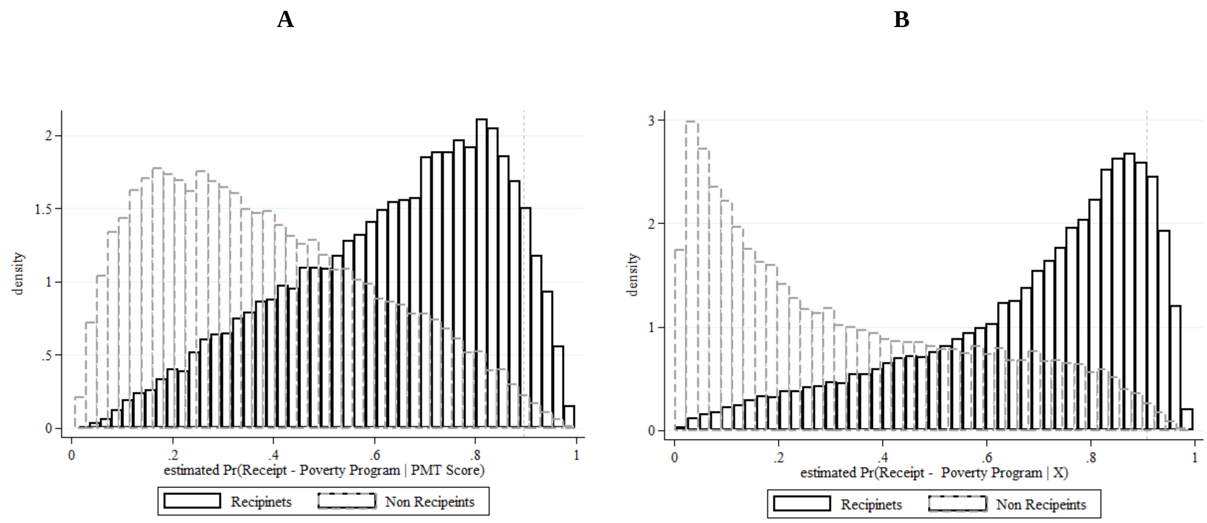
Figure 3. Time Horizon of Data Collection in the Periods between 2013 and 2014



This figure shows the time line of data collections which are utilized in this study. This study use unique dataset that was collected specifically for the evaluation of poverty targeting and the delivery of poverty programs in Indonesia, namely the SPS (for *Survei Perlindungan Sosial* or Social Protection Survey) which is combined with Official PMT coefficient used by the GoI in selecting the beneficiaries of each poverty programs and other dataset (e.g. PODES and SUSENAS).

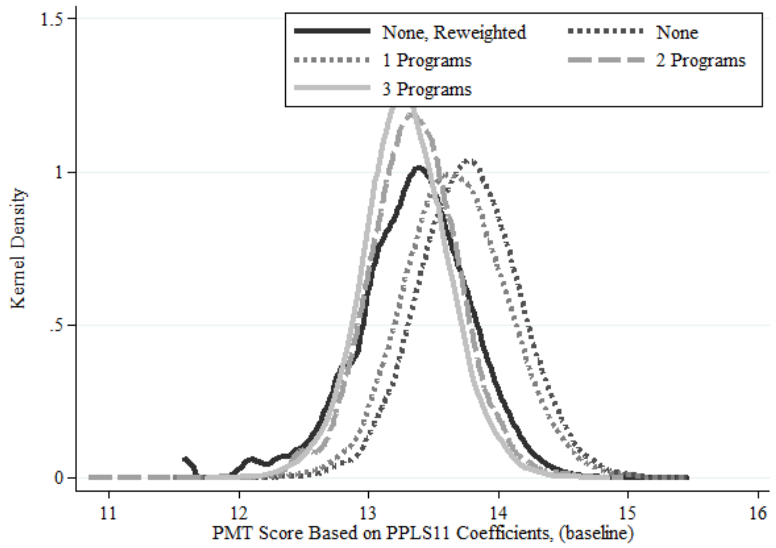
Source: Author tabulation from multiple sources of the GoI official documents such as the guideline of SUSENAS Survey, Social Protection Survey, Podes, and others. Note: The blue dotes denote the periods of SUSENAS survey.

Figure 4. Estimation of Propensity Score based on PMT Score and Underlying Covariates



This figure presents the overlap of Propensity Score ($\hat{p}$). The panel A is estimated using PMT score as a single covariate. While the panel B is estimated using underlying covariates as presented in Table A3 in the appendix.

Figure 5. Baseline of PMT score across treatment level



'None' is the distribution of households that did not receive any poverty programs, while 'one', 'two', or 'three' rather denote how many poverty programs were received by households. 'None, reweighted', is the distribution of households that received nothing adjusted by the inverse probability weights, $\widehat{\omega}$.

Table 1 Targeting Matrix of the Complementary Multiple Programs

		Poverty Status		Total
		Poor	Non-poor	
Beneficiaries status of program BLT	Beneficiary	Correct of inclusion ($C1_B$)	Error of Inclusion ($E1_B$)	B_B
	Non- beneficiary	Error of Exclusion ($E2_B$)	Correct Exclusion ($C2_B$)	NB_B
Beneficiaries status of program *Raskin*	Beneficiary	Correct of inclusion ($C1_R$)	Error of Inclusion ($E1_R$)	B_R
	Non- beneficiary	Error of Exclusion ($E2_R$)	Correct Exclusion ($C2_R$)	NB_R
Beneficiaries status of program *Jamkesmas*	Beneficiary	Correct of inclusion ($C1_J$)	Error of Inclusion ($E1_J$)	B_J
	Non- beneficiary	Error of Exclusion ($E2_J$)	Correct Exclusion ($C2_J$)	NB_J
		P	NP	T

This table represent an extension of the standard matrix used in evaluation the performance of poverty targeting. The information about the standard matrix can be found in studies by Coady, Grosh, and Hoddinott, (2004).

Table 2. Joint and marginal probabilities of poor households receiving poverty programs

	Joint probability	Marginal (BLT)	Marginal (*Raskin*)	Marginal (*Jamkesmas*)	Total
(1)	(2)	(3)	(4)	(5)	
BLT only	$(C_{B=1,R=0,J=0}/P)$	$(C_{B=1,R=0,J=0}/P)$	-	-	
Raskin only	$(C_{B=0,R=1,J=0}/P)$	-	$(C_{B=0,R=1,J=0}/P)$	-	
Jamkesmas only	$(C_{B=0,R=0,J=1}/P)$	-	-	$(C_{B=0,R=0,J=1}/P)$	
BLT and *Raskin* only	$(C_{B=1,R=1,J=0}/P)$	$(C_{B=1,R=1,J=0}/P)$	$(C_{B=1,R=1,J=0}/P)$		
BLT and *Jamkesmas* only	$(C_{B=1,J=1,R=0}/P)$	$(C_{B=1,J=1,R=0}/P)$	-	$(C_{B=1,J=1,R=0}/P)$	
Raskin and *Jamkesmas* only	$(C_{R=1,J=1,B=0}/P)$	-	$(C_{R=1,J=1,B=0}/P)$	$(C_{R=1,J=1,B=0}/P)$	
BLT, *Raskin* and *Jamkesmas*	$(C_{B=1,R=1,J=1}/P)$	$(C_{B=1,R=1,J=1}/P)$	$(C_{B=1,R=1,J=1}/P)$	$(C_{B=1,R=1,J=1}/P)$	
None	$(C_{B=0,R=0,J=0}/P)$	-	-	-	ee_T
Total	100	$C1_B/P$	$C1_R/P$	$C1_J/P$	

This table is constructed using information from Table 1 to measure the degree of complementarity of each program with respect to the others. For example, under perfect complementarities, the joint probability of poor households receiving three programs will be equal to the total marginal probability for all programs. This implies that under this condition, the joint probability for poor households receiving either one or two programs will be zero.

Table 3 Observed joint and marginal probabilities of the poor household receiving the poverty programs

Targeting Methods →	2005[a]				2009[a]				2014[b]			
Probabilities →	Joint	Marginal			Joint	Marginal			Joint	Marginal		
Programs ↓		BLT	*Raskin*	*Jamkesmas*		BLT	*Raskin*	*Jamkesmas*		BLT	*Raskin*	*Jamkesmas*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BLT only	7.89	7.89			4.76	4.76			3.96	3.96		
Raskin only	18.28		18.28		23.74		23.74		19.66		19.66	
Jamkesmas only	0.93			0.93	1.55			1.55	4.49			4.49
BLT and *Raskin* only	30.96	30.96	30.96		24.78	24.78	24.78		9.42	9.42	9.42	
BLT and *Jamkesmas* only	1.73	1.73		1.73	1.61	1.61		1.61	8.21	8.21		8.21
Raskin and *Jamkesmas* only	2.93		2.93	2.93	3.53		3.53	3.53	9.20		9.20	9.20
BLT, *Raskin* and *Jamkesmas*	15.66	15.66	15.66	15.66	12.67	12.67	12.67	12.67	27.51	27.51	27.51	27.51
None	21.62				27.36				17.55			
Total	100.00	56.24	67.83	21.25	100.00	43.82	64.72	19.36	100.00	49.10	65.79	49.41

This table present the joint and marginal probability of poor households receiving either one, two or the program which is measured using the formula presented in Table 2. Source: Authors' calculation. Note: a) are measured using SUSENAS 2006 and 2009; b) is measured using SUSENAS and Social Protection Survey (SPS) 2014.

Table 4 Observed conditional and unconditional probabilities of poor households receiving poverty programs based on different targeting methods

Targeting Methods →	2005[a]			2009[a]			2014[b]		
Probabilities →	BLT	*Raskin*	*Jamkesmas*	BLT	*Raskin*	*Jamkesmas*	BLT	*Raskin*	*Jamkesmas*
Programs ↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
P(.)	56.24	67.83	21.25	43.82	64.72	19.36	49.10	65.79	49.41
P(. |BLT = 1)	100.00	82.89	30.92	100.00	85.46	32.59	100.00	75.21	72.75
P(. |*Raskin* = 1)	68.73	100.00	27.41	57.86	100.00	25.03	56.13	100.00	55.80
P(. |*Jamkesmas* = 1)	81.84	87.48	100.00	73.76	83.68	100.00	72.29	74.30	100.00
P(. |*Raskin* = 1, *Jamkesmas* = 1)	84.24	100.00	100.00	78.21	100.00	100.00	74.94	100.00	100.00
P(. |BLT = 1, *Jamkesmas* = 1)	100.00	90.05	100.00	100.00	88.73	100.00	100.00	77.02	100.00
P(. |BLT = 1, *Raskin* = 1)	100.00	100.00	33.59	100.00	100.00	33.83	100.00	100.00	74.49

This table presents conditional and unconditional probabilities measured based on information in Table 3. The number on each cell of the table is derived using formula presented in either Equation (1), 2, 3, or 4 depending its condition. Note: a) are measured using SUSENAS 2006 and 2009; b) is measured using SUSENAS and Social Protection Survey (SPS) 2014.

Table 5. Observed joint and marginal probabilities of the poor household receiving the poverty programs in 2014 (with or without KPS)

Years →	Poor Households - **All Sample**				Poor Households - **with KPS**				Poor Households - **without KPS**			
Probabilities →	Joint	Marginal Probabilities			Joint	Marginal Probabilities			Joint	Marginal Probabilities		
Programs ↓		BLT	*Raskin*	*Jamkesmas*		BLT	*Raskin*	*Jamkesmas*		BLT	*Raskin*	*Jamkesmas*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BLT only	3.96	3.96			6.52	6.52			1.89	1.89		
Raskin only	19.66		19.66		0.67		0.67		35.02		35.02	
Jamkesmas only	4.49			4.49	1.20			1.20	7.14			7.14
BLT and *Raskin* only	9.42	9.42	9.42		16.62	16.62	16.62		3.60	3.60	3.60	
BLT and *Jamkesmas* only	8.21	8.21		8.21	16.32	16.32		16.32	1.65	1.65		1.65
Raskin and *Jamkesmas* only	9.20		9.20	9.20	1.44		1.44	1.44	15.48		15.48	15.48
BLT, *Raskin* and *Jamkesmas*	27.51	27.51	27.51	27.51	56.79	56.79	56.79	56.79	3.83	3.83	3.83	3.83
None	17.55				0.44				31.39			
Total	100.00	49.10	65.79	49.41	100.00	96.25	75.52	75.75	100.00	10.97	57.93	28.10

This Table present probabilities measured as in Table 4 with dividing the sample becomes either the households received KPS or did not. Note: This probabilities are measured using SUSENAS and Social Protection Survey (SPS) 2014.

Table 6. Observed conditional and unconditional probabilities of the poor household receiving the poverty programs in 2014 (with or without KPS)

Years →	Poor Households - **All Sample**			Poor Households **- with KPS**			Poor Households **- without KPS**		
Probabilities →	BLT	*Raskin*	*Jamkesmas*	BLT	*Raskin*	*Jamkesmas*	BLT	*Raskin*	*Jamkesmas*
Programs ↓	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
P(.)	49.10	65.79	49.41	96.25	75.52	75.75	10.97	57.93	28.10
P(. |BLT = 1)	100.00	75.21	72.75	100.00	76.27	75.96	100.00	67.73	49.95
P(. |*Raskin* = 1)	56.13	100.00	55.80	97.21	100.00	77.11	12.83	100.00	33.33
P(. |*Jamkesmas* = 1)	72.29	74.30	100.00	96.51	76.87	100.00	19.50	68.72	100.00
P(. |R*askin* = 1, *Jamkesmas* = 1)	74.94	100.00	100.00	97.53	100.00	100.00	19.83	100.00	100.00
P(. |BLT = 1, *Jamkesmas* = 1)	100.00	77.02	100.00	100.00	77.68	100.00	100.00	69.89	100.00
P(. |BLT = 1, *Raskin* = 1)	100.00	100.00	74.49	100.00	100.00	77.36	100.00	100.00	51.55

This table present probabilities measured as in Table 5 with dividing the sample becomes either the households received KPS or did not. This probabilities are measured using SUSENAS and Social Protection Survey (SPS) 2014.

Table 7 Difference on Per Capita Expenditure

Estimator	OLS	IPW	Double Robustness ($\hat{p}_h$)	Double Robustness (PMT_h)	Control Function
	(1)	(2)	(3)	(4)	(5)
3 Programs vs. None					
$\boldsymbol{\theta_3}$	0.085	0.085	0.126	0.126	0.143
	(0.012)***	(0.012)***	(0.012)***	(0.012)***	(0.012)***
$\boldsymbol{\theta_0}$	-0.248	-0.284	-0.274	-0.274	-0.190
	(0.009)***	(0.010)***	(0.009)***	(0.009)***	(0.011)***
$\boldsymbol{\theta_{30}}$	**0.333**	**0.369**	**0.400**	**0.400**	**0.332**
	(0.013)***	(0.014)***	(0.013)***	(0.014)***	(0.013)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.154	0.159	0.178	0.178	0.184
2 Programs vs. None					
$\boldsymbol{\theta_2}$	0.036	0.034	0.053	0.052	0.058
	(0.010)***	(0.010)***	(0.011)***	(0.011)***	(0.011)***
$\boldsymbol{\theta_0}$	-0.256	-0.293	-0.287	-0.287	-0.204
	(0.009)***	(0.009)***	(0.010)***	(0.009)***	(0.012)***
$\boldsymbol{\theta_{20}}$	**0.292**	**0.327**	**0.340**	**0.339**	**0.262**
	(0.011)***	(0.012)***	(0.013)***	(0.013)***	(0.013)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.153	0.158	0.177	0.176	0.182
1 Program vs. None					
$\boldsymbol{\theta_1}$	-0.068	-0.064	-0.104	-0.105	-0.130
	(0.010)***	(0.010)***	(0.011)***	(0.010)***	(0.010)***
$\boldsymbol{\theta_0}$	-0.300	-0.334	-0.353	-0.352	-0.276
	(0.010)***	(0.011)***	(0.012)***	(0.012)***	(0.012)***
$\boldsymbol{\theta_{10}}$	**0.232**	**0.270**	**0.248**	**0.248**	**0.146**
	(0.009)***	(0.010)***	(0.010)***	(0.010)***	(0.012)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.154	0.159	0.179	0.178	0.185

Notes: the dependent variable is the difference log total per capita expenditure between before and after treatment. The first column denotes the pure OLS estimation, while the next column is the results of IPW estimator. Column 3 and 4 are the double robustness estimation which is proposed by Scharfstein et al. (1999), and column 5 is the five-subclass estimation following Rosenbaum and Rubin (1984). The standard errors (presented in parentheses) in column 2-5 are clustered by the village and computed over the entire two-step using a block bootstrap with 500 repetitions following Cameron et. al, 2008. *** p<0.01, ** p<0.05, * p<0.1.

Table 8 Difference on Poverty Gap Index (FGT)

Estimator	OLS	IPW	Double Robustness $(\hat{p}_h)$	Double Robustness (PMT_h)	Control Function
	(1)	(2)	(3)	(4)	(5)
3 Programs vs. None					
$\boldsymbol{\theta_{33}}$	-0.017	-0.017	-0.010	-0.009	-0.009
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
$\boldsymbol{\theta_{00}}$	0.019	0.007	0.008	0.008	0.026
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***
$\boldsymbol{\theta_{30}}$	**-0.0358**	**-0.023**	**-0.018**	**-0.018**	**-0.035**
	(0.001)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.057	0.0561	0.103	0.107	0.112
2 Programs vs. None					
$\boldsymbol{\theta_{23}}$	-0.010	-0.008	-0.005	-0.005	-0.006
	(0.001)***	(0.002)***	(0.002)***	(0.002)***	(0.001)***
$\boldsymbol{\theta_{00}}$	0.020	0.008	0.009	0.009	0.027
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***
$\boldsymbol{\theta_{20}}$	**-0.0298**	**-0.016**	**-0.014**	**-0.014**	**-0.032**
	(0.001)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.054	0.0538	0.103	0.106	0.112
1 Programs vs. None					
$\boldsymbol{\theta_{13}}$	0.018	0.018	0.011	0.010	0.009
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
$\boldsymbol{\theta_{00}}$	0.031	0.019	0.016	0.015	0.032
	(0.001)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
$\boldsymbol{\theta_{10}}$	**-0.0137**	**-0.001**	**-0.005**	**-0.005**	**-0.023**
	(0.001)***	(0.001)	(0.001)***	(0.001)***	(0.002)***
Reweighted	No	Yes	Yes	Yes	Yes
Propensity Score Control	No	No	Yes	No	Yes
PMT score control	No	No	No	Yes	No
Number of Households	63,681	67,118	67,118	67,118	67,118
$\boldsymbol{R^2}$	0.060	0.0589	0.104	0.108	0.113

Notes: the dependent variable is the difference of Poverty Gap Index (FGT1) between 2011 and March 2014. All conditions used in the estimation can be seen in Table 11. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 Matrix Comparison – Combination between Treatments and Controls using Control Function Estimation

	None	3 Programs	2 Program	1 Program	BLT and *Raskin* only	BLT and *Jamkesmas* only	*Raskin* and *Jamkesmas* only	BLT only	*Raskin* only	*Jamkesmas* only
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
None		0.316	0.247	0.128	0.245	0.274	0.232	0.162	0.129	0.136
		(0.014)***	(0.012)***	(0.011)***	(0.019)***	(0.020)***	(0.016)***	(0.038)***	(0.012)***	(0.019)***
3 Programs	0.316		0.0731	0.184	0.0709	0.0395	0.0896	0.160	0.185	0.189
	(0.014)***		(0.013)***	(0.013)***	(0.020)***	(0.022)***	(0.016)***	(0.040)***	(0.013)***	(0.021)***
2 Programs	0.247	0.0731		0.110				0.0820	0.112	0.111
	(0.012)***	(0.013)***		(0.011)***				(0.039)**	(0.012)***	(0.020)***
1 Programs	0.128	0.184	0.110		0.112	0.145	0.0920			
	(0.011)***	(0.013)***	(0.011)***		(0.019)***	(0.020)***	(0.014)***			
BLT and *Raskin* only	0.245	0.0709		0.112		0.0514	0.0185	0.0837	0.114	0.114
	(0.019)***	(0.020)***		(0.019)***		(0.023)**	(0.022)	(0.041)**	(0.019)***	(0.025)***
BLT and *Jamkesmas* only	0.274	0.0395		0.145	0.0514		0.0329	0.117	0.148	0.143
	(0.020)***	(0.022)***		(0.020)***	(0.023)**		(0.026)	(0.042)***	(0.021)***	(0.024)***
Raskin and *Jamkesmas* only	0.232	0.0896		0.0920	0.0185	0.0329		0.068	0.093	0.095
	(0.016)***	(0.016)***		(0.014)***	(0.022)	(0.026)		(0.041)*	(0.015)***	(0.023)***
BLT only	0.162	0.160	0.0820		0.0837	0.117	0.068		0.029	0.028
	(0.038)***	(0.040)***	(0.039)**		(0.041)**	(0.042)***	(0.041)*		(0.039)	(0.042)
Raskin only	0.129	0.185	0.112		0.114	0.148	0.093	0.029		0.000
	(0.012)***	(0.013)***	(0.012)***		(0.019)***	(0.021)***	(0.015)***	(0.039)		(0.020)
Jamkesmas only	0.136	0.189	0.111		0.114	0.143	0.095	0.028	0.000	
	(0.019)***	(0.021)***	(0.020)***		(0.025)***	(0.024)***	(0.023)***	(0.042)	(0.020)	

Notes: the dependent variable is the difference log total per capita expenditure between before and after treatment. All estimations are conducted under five-subclass estimation following Rosenbaum and Rubin (1984). *** p<0.01, ** p<0.05, * p<0.1.

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Appendixes

Table A1 Household Characteristics by Receiving Poverty Program

	Non-Receiving Program		Receiving Program		Difference	
PMT Score	13.616	(0.43)	13.492	(0.352)	-0.100***	[0.013]
Percapita Expenditure ('000)	913.84	(1034)	632.980	(529.81)	-239707***	[24571]
Head of Household Characteristics						
Male	0.858	(0.349)	0.842	(0.364)	-0.012*	[0.007]
Married	0.818	(0.386)	0.813	(0.390)	-0.005	[0.007]
Age	47.676	(13.568)	48.811	(13.737)	0.789***	[0.179]
Education						
Elementary	0.202	(0.401)	0.248	(0.432)	0.042***	[0.008]
Junior High	0.206	(0.405)	0.247	(0.431)	0.037***	[0.005]
Senior High & University	0.415	(0.493)	0.299	(0.458)	-0.106***	[0.012]
Working Status: Employed	0.879	(0.326)	0.893	(0.310)	0.015***	[0.005]
Employment Sector:						
Agriculture	0.362	(0.481)	0.457	(0.498)	0.098***	[0.010]
Mining & Quarrying	0.020	(0.139)	0.015	(0.122)	-0.000	[0.002]
Processing Industry	0.063	(0.242)	0.068	(0.251)	-0.001	[0.003]
Trading	0.128	(0.334)	0.112	(0.315)	-0.016***	[0.004]
Construction/building	0.067	(0.249)	0.078	(0.268)	0.010**	[0.004]
Hotel & Restaurant	0.013	(0.115)	0.009	(0.097)	-0.004***	[0.001]
Transportation & ICT	0.050	(0.218)	0.047	(0.212)	-0.002	[0.003]
Household Characteristics						
Size (Person)	3.878	(1.725)	3.787	(1.687)	-0.056**	[0.021]
Dependency ratio	0.654	(0.649)	0.650	(0.651)	-0.004	[0.010]
Number of Household Member: 0-4 yrs	0.336	(0.568)	0.334	(0.554)	0.003	[0.005]
Number of Household Member at School Age						
Elementary	0.527	(0.737)	0.471	(0.696)	-0.043***	[0.010]
Junior High	0.218	(0.457)	0.201	(0.440)	-0.013***	[0.004]
Senior High	0.160	(0.405)	0.138	(0.371)	-0.019***	[0.003]
University	0.076	(0.308)	0.039	(0.217)	-0.035***	[0.004]
Assets						
Bicycle	0.327	(0.469)	0.321	(0.467)	-0.030***	[0.008]
Gas ≥ 3 kg	0.148	(0.355)	0.043	(0.203)	-0.091***	[0.010]
Refrigerator	0.445	(0.497)	0.298	(0.458)	-0.128***	[0.014]
Motorcycle	0.671	(0.470)	0.627	(0.484)	-0.041**	[0.015]
Water Access						
Branded/Recycled Bottle Water	0.290	(0.454)	0.163	(0.369)	-0.106***	[0.011]
Pipe with Meter	0.121	(0.326)	0.094	(0.292)	-0.025***	[0.008]
Terrestrial well/pump	0.119	(0.323)	0.143	(0.350)	0.012*	[0.006]
Protected/Covered well	0.197	(0.398)	0.254	(0.435)	0.038***	[0.008]
Unprotected/Uncovered well	0.274	(0.446)	0.346	(0.476)	0.082***	[0.011]
From buying from other parties	0.444	(0.497)	0.312	(0.463)	-0.115***	[0.009]
Housing						
Own	0.799	(0.401)	0.864	(0.342)	0.049***	[0.006]
rent	0.036	(0.186)	0.015	(0.123)	-0.017***	[0.002]
Lease	0.046	(0.210)	0.018	(0.131)	-0.021***	[0.003]
Company House	0.024	(0.152)	0.006	(0.078)	-0.015***	[0.003]
Others	0.096	(0.294)	0.096	(0.295)	0.004	[0.005]

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	Non-Receiving Program		Receiving Program		Difference	
Lighting Sources						
PLN Electricity 450 W	0.784	(0.412)	0.759	(0.427)	-0.030**	[0.013]
PLN Electricity without Meter	0.104	(0.306)	0.120	(0.325)	0.008	[0.007]
Non-PLN Electricity	0.050	(0.218)	0.047	(0.212)	0.004	[0.005]
Non-Electricity	0.062	(0.241)	0.073	(0.261)	0.019***	[0.006]
Final disposal						
Septic Tank	0.624	(0.484)	0.554	(0.497)	-0.067***	[0.014]
Pit hole	0.118	(0.322)	0.147	(0.354)	0.026***	[0.008]
River/Lake/Sea	0.176	(0.380)	0.195	(0.396)	0.018**	[0.007]
Beach/open field/farm	0.064	(0.245)	0.078	(0.269)	0.019***	[0.006]
Defecation facility use						
Personal	0.715	(0.451)	0.657	(0.475)	-0.053***	[0.016]
Mutual	0.285	(0.451)	0.343	(0.475)	0.053***	[0.016]
House Characteristics						
Wall material: Concrete	0.624	(0.484)	0.597	(0.491)	-0.057***	[0.017]
Wall material: Wood	0.376	(0.484)	0.403	(0.491)	0.057***	[0.017]
Roof Materials: Concrete	0.025	(0.156)	0.017	(0.127)	-0.008***	[0.002]
Roof Materials: Roof Tile	0.370	(0.483)	0.477	(0.500)	0.007	[0.007]
Roof Materials: Iron Sheet/Asbeston	0.546	(0.498)	0.445	(0.497)	-0.009	[0.008]
Roof Materials: Shingle/Fiber/Palm	0.059	(0.235)	0.061	(0.240)	0.011	[0.006]
Number of Households	50,043		17,075		67,118	

This table present the mean tests of the characteristics of households who received the poverty program and did not. Number inside the parentheses is the standard deviation, while inside the square brackets denote the standard error. ***p<0.01, **p<0.05, * p<0.1.

Table A2 Village Characteristics by Receiving Poverty Program

	Non-Receiving Program		Receiving Program		Difference	
Village Characteristics						
Rural area	0.650	0.477	0.819	0.385	0.142***	[0.011]
Distance to the nearest						
Market (Km)	6.968	16.655	7.587	17.647	1.259**	[0.583]
Health Facility (Km)	5.098	11.853	6.168	13.250	1.318***	[0.311]
Sub-district office (Km)	6.261	25.432	6.803	20.573	0.699	[0.438]
District office (Km)	29.843	53.452	34.582	47.342	6.132***	[1.708]
Village has:						
Shophouse	0.340	0.474	0.223	0.416	-0.117***	[0.011]
Hotel	0.152	0.359	0.074	0.262	-0.065***	[0.007]
Cooperation	0.525	0.499	0.472	0.499	-0.062***	[0.009]
Credit Finance	0.502	0.500	0.496	0.500	-0.025***	[0.008]
Access to the Bank	0.297	0.457	0.180	0.384	-0.105***	[0.010]
School building						
Elementary	0.947	0.224	0.947	0.223	-0.002	[0.003]
Junior High School	0.609	0.488	0.552	0.497	-0.054***	[0.008]
Senior High School	0.435	0.496	0.332	0.471	-0.095***	[0.008]
Village Health Facility (*Polindes*)	0.460	0.498	0.519	0.500	0.034***	[0.009]
Sub-Vil. Health Facility (*Posyandu*)	0.978	0.147	0.977	0.151	-0.003	[0.003]

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	Non-Receiving Program		Receiving Program		Difference	
Asphalt Road	0.782	0.413	0.730	0.444	-0.060***	[0.010]
Road can be accessed 4-wheel car	0.929	0.257	0.913	0.282	-0.026***	[0.008]
Head of Village Characteristics						
Gender: Male	0.910	0.286	0.933	0.250	0.019***	[0.004]
Age (years old)	44.067	10.150	44.321	9.507	0.019	[0.176]
Education background						
No Education	0.014	0.116	0.019	0.135	0.005**	[0.002]
Elementary	0.017	0.128	0.018	0.133	0.002	[0.002]
Junior High School	0.101	0.302	0.137	0.344	0.032***	[0.007]
Senior High School	0.456	0.498	0.512	0.500	0.051***	[0.010]
University	0.040	0.196	0.044	0.204	0.001	[0.003]
Number of Households	50043		17075		67,118	

This table present the mean tests of the village characteristics where the households who received the poverty program and did not. Number inside the parentheses is the standard deviation, while inside the square brackets denote the standard error. ***p<0.01, **p<0.05, * p<0.1.

Table A3 Underlying Variables of PMT Score

	dy/dx	(S.E)		dy/dx	(S.E)
Head of HHD: Male	-0.099	(0.014)***	*Primary income source (reference = other)*		
Married Status Head of HHD	0.042	(0.012)***	Head of HHD working	-0.017	(0.014)
h_hhsize	0.058	(0.004)***	Agriculture	0.111	(0.016)***
Age of Head of HHD	0.000	(0.001)	Mining and Quarrying	0.092	(0.034)***
# HHD member 0-4 years	-0.021	(0.009)**	Processing Industry	0.110	(0.023)***
Dependency Ratio	0.008	(0.007)	Trading	0.060	(0.015)***
			Construction/building	0.189	(0.016)***
Household head education level (reference = No education)			Hotel and Restaurant	0.011	(0.028)
Elementary	-0.073	(0.010)***	Transportation and warehousing	0.115	(0.016)***
Junior High	-0.126	(0.017)***	Public service	0.054	(0.012)***
High School - S3	-0.291	(0.022)***			
			Self-Owned business	0.014	(0.009)
Highest Education Background in the Household (reference: No education)			Self-Owned business with non-permanent worker	-0.013	(0.011)
Elementary	0.056	(0.011)***	Self-Owned business with permanent worker	-0.124	(0.020)***
Junior High	0.056	(0.009)***			
Senior High - S3	-0.059	(0.010)***	*Home ownership Status (reference = Other)*		
			Own	-0.019	(0.014)
Number of Household members who are studying at:			rent	-0.207	(0.038)***
Elementary	0.000	(0.005)	Lease	-0.279	(0.033)***
Junior High	0.002	(0.007)	Company House	-0.332	(0.073)***
Senior High	-0.024	(0.009)**			
University	-0.063	(0.014)***	*Source of Ligthing (Reference = No Electricity)*		
			Source of Lighting:	0.059	(0.040)
			PLN Electricity without Meter	0.124	(0.042)***
			Non-PLN Electricity	0.002	(0.030)

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	dy/dx	(S.E)		dy/dx	(S.E)
Household Assets:			Final Disposal Location (Reference = Other)		
Bicycle	0.004	(0.008)	Septic Tank	-0.060	(0.026)**
gas >= 12 kg	-0.262	(0.019)***	River/Lake/Sea	-0.015	(0.028)
Refrigerator	-0.164	(0.014)***	Pit hole	-0.032	(0.024)
Motorcycle	-0.092	(0.011)***	Beach/open field/farm	-0.038	(0.026)
			River/Lake/Sea	-0.015	(0.028)
Source of Drinking Water (reference = Unprotected well)			Pit hole	-0.032	(0.024)
Branded/Recycled Bottle Water	-0.124	(0.016)***	Beach/open field/farm	-0.038	(0.026)
Pipe with Meter	-0.065	(0.024)***			
Terrestrial well/pump	-0.027	(0.018)	*Defecation facility use (Reference = mutual)*		
Protected/Covered well	0.005	(0.014)	Personal	-0.083	(0.013)***
Buying	0.007	(0.011)			
			Type of wall material (reference = wood)		
Roof Materials (Reference = Shingle/Fiber/Palm)			Type of wall material: Concrete	-0.099	(0.010)***
Concrete	-0.073	(0.037)**			
Roof Tile	-0.013	(0.043)	Type of flooring material: Not Soil	-0.076	(0.056)
Iron Sheet/Asbeston	-0.027	(0.032)			
Pseudo R2	0.2953				
Households	67,118				

This table presents the marginal effect of Probit estimation. The dependent variable is 1 if the household receive any poverty programs, 0 otherwise. Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

Figure A1 The Evolution of the Social Protection Programs in Indonesia: The First and Second Generations