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ABSTRACT

Does Information Empower the Poor? Evidence from Indonesia's Social Security Card*

In 2013, the Government of Indonesia conducted one of the largest information interventions in histo-ry, in an attempt to further alleviate poverty and as a complement to the Social Protection Card (KPS). Drawing upon administrative data and nationally representative surveys, we evaluate the impact of the information campaign on the receipt of two of Indonesia's largest social programs, the Raskin (rice for the poor) and the BLSM (temporary unconditional cash transfers). Exploiting the design of the *Raskin* program, we implement a (normalised) fuzzy regression discontinuity methodology across 482 Indonesian districts, using program eligibility as an instrument for having received the information treatment. Further corroborating our results with semi-parametric and parametric techniques, we show that the information treatment increases the amount of rice received under the Raskin program by around 30 percentage points. In terms of the BLSM, we further show that the information treatment reduces the likelihood of elite capture by local leaders by around 25 percentage points. We also provide evidence that *understanding* the information treatment is crucial for poor household's out-comes, since fully informed households receive their full entitlement of rice.

JEL Classification: D04, D73, I32, I38, O12

Keywords: poverty, targeting, Indonesia, information

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"Knowledge is power. Information is liberating. Education is the premise of progress, in every society, in every family"

Kofi Annan

Poor households in developing countries typically do not have access to complete information about their rights to social welfare programs. This constrains such households' ability to fully benefit from social programs aimed at poverty reduction. In addressing this challenge, the World Bank has championed greater dissemination of information on various poverty programs among social welfare recipients to empower the poor (World Bank 2004). In recent years, governments in several developing countries, including Indonesia, have implemented various strategies to inform potential recipients on their eligibility for programs as well as their level of benefit entitlements. Their aim is to improve both the transparency and accountability of service delivery from poverty programs using information-based interventions. In this paper, we evaluate the largest such information campaign in Indonesia using nationally representative administrative data.

The prominent role of access to information has been firmly established in seminal research by Stigler (1961) and Akerlof (1970). When governments represent monopoly providers of services, access to information allows the public to improve the accountability of those programs, thereby reducing the potential for local capture and mismanagement of public resources (World Bank 2004, Kosack and Fung 2014). A recent study by Banerjee et al. (forthcoming) however, also warns that too much information can be counterproductive, since it may place local leaders under greater pressure thereby reducing their willingness to fully implement programs**.**

Despite the potentially crucial importance of information provision for successful targeting social programs to the poor, the existing literature focuses almost exclusively on analysing the provision of information in alternative contexts. Their results have largely been inconclusive. Studies by Reinikka and Svensson (2004) in Uganda, and Pandey, Goyal and Sundararaman (2009) in India for example, find that access to information on these programs contributed positively to education-related outcomes. Others however, such as Banerjee et al. (2010) in India, Pradhan et al. (2014) in Indonesia, and Lieberman and Posner and Tsai (2014) in Kenya, fail to uncover any statistically significant impact of information on the quality of children's schooling Olken's (2007) study from Indonesia, finds that disseminating information locally reduced leakage from road project funds, although he also notes that increased public participation in monitoring had no discernible impact on the same outcome. It remains unclear why some information-based interventions succeed in improving service delivery, while others do not. One possible explanation relates to the extent to which information is understood by eligible households (Fox 2007). Previous research, with the exception of Ravallion et al. (2013), assumes that targeted households fully understand the information content provided to them. To the best of our knowledge, there are only two studies that evaluate information-based interventions in poverty programs, both of which use field experiments.

Ravallion et al. (2013) evaluate the impact of an information intervention consisting of a 25-minute long video on India's National Rural Employment Guarantee Act (NREGA). They conclude that the intervention to disseminate information about the NREGA had no discernible impact on individuals seeking and obtaining employment, although the intervention furthered citizens' knowledge about their rights and entitlements to employment opportunities under the NREGA. In a similar vein, Banerjee et al. (forthcoming) implement field experiments across six Indonesian districts. They find that households treated with information received 26% more subsidy (under the auspices of the Raskin program).[1,2] The authors argue that the increased benefits were driven by an improvement in recipients' awareness and ability to bargain with village leaders, as opposed to leaders more assiduously complying with program rules.

In this paper we evaluate the impact of household's access to and understanding of information on the intensive margin of benefit received under two of Indonesia's largest social welfare programs, Raskin and BLSM.[3] The KPS program, one of the largest (information) interventions

[1] *Raskin* (*Beras untuk Keluarga Miskin* or Rice for the Poor) is one of the poverty programs aimed at targeted households, which seeks to reduce household spending on food, especially on rice. Before 2002, this program was called OPK (for *Operasi Pasar Khusus* or Special Market Operation program).

[2] This study can be seen as a pilot project for the KPS. Together with the GoI, these authors implemented a field experiment in 378 villages (randomly selected from among 572 villages spread across three provinces). The GoI sent the "*Raskin* identification cards" to eligible households to inform them of their program eligibility in addition to information about the amount of benefit they should receive. Ravallion (2008), however, argues that partial equilibrium assumptions may hold for a pilot study, but that general equilibrium effects (sometimes called "feedback" or "macro" effects in the evaluation literature) may play more prominent roles when such interventions are scaled up nationally. This paper can therefore be considered a complement to Banerjee et al. (forthcoming) in terms of providing the overall (general equilibrium) effects.

[3] BLSM (for *Bantuan Langsung Sementara Masyarakat* or Temporary Unconditional Cash Transfer program) is an unconditional cash transfer that was introduced for the first time in 2005 known as BLT (*Bantuan Langsung Tunai* - or Direct Cash Assistance). The program was implemented by the GoI as one of compensation schemes to subsidise for oil prices.

in the history of poverty reduction programs, seeks to provide eligible households with information about various social welfare programs in addition to detailing the amount of benefits households are entitled to (see Tohari et al. (2017) for further details). The KPS card was issued to approximately 25% of the poorest Indonesian households (equivalent to 15.5 million of beneficiaries) as identified by their rank in the Unified Database System (UDB). KPS card-holding households are entitled to *Raskin*, temporary unconditional cash transfers (BLSM) and financial assistance for student family members (TNP2K, 2015a). The KPS card therefore confirms eligibility status, while the KPS program additionally provided information about Indonesia's social programs to entitled households.

This information campaign was delivered through various media outlets including television, radio and internet, as well as by local government. We contribute to the literature by evaluating the KPS information treatment using nationally representative administrative data. Specifically we exploit the programs' designs to establish causal inference of the impacts of information provision as well as individuals' understanding of information on the intensive margins of benefit received from two of Indonesia's largest social welfare programs, namely Raskin and BLSM. These are the only two programs that can be examined in this context due to the design and specific questions asked in the Social Protection Survey (SPS).[4] Using all 482 official Proxy Mean Test (PMT) thresholds (i.e. PMT coefficients)[5] and cut-offs used by the Government of Indonesia (GoI) to identify households' eligability, we subsqeuently exploit the resulting discontinuity using a range of parametric, semiparametric and non-parametric methods.

Importantly, as shown in Table A.3. in the Appendix, not all eligible households received the information treatment, and some ineligible households also received information on the programs. Our initial information treatment therefore is whether a household is both eligible for the KPS and received information (we aggregate complete and incomplete information-treated households). The remainder or our sample in the initial estimation therefore comprises

[4] SPS (for *Survei Perlindungan Sosial* or Social Protection Survey) was conducted together by TNP2K and BPS in the period from first quarter of 2013 to first quarter of 2014 as a supplement for regular SUSENAS for Survei Sosial Ekonomi Nasional or National Socioeconomic Survey). This survey aimed to evaluate the performance of poverty targeting and the implementation poverty alleviation programs, especially for the implementation of UDB and the KPS).

[5] Proxy means testing is often used for targeting poverty programs in developing countries. The method assigns a score to all potential participants as a function of observed characteristics. When strictly applied, the program is assigned if and only if a unit's score is below some critical level, as determined by the budget allocation of the scheme (Ravallion, 2007).

ineligible households that also received the information. Based on their eligibility (for KPS), 63.97% of households in the sample who received the information are eligible. Our study differs from Banerjee et al. (forthcoming) in several ways: (1) we evaluate two programs nationwide as opposed to a single program using a smaller sample (2) we provide evidence of an alternative causal mechanism via which information interventions affect poor household's outcomes and finally (3) we are able to gauge the impacts of both information provision and understanding the content of the information provided.

Our results show that households treated with information provision received 30 percentage points more rice under the Raskin program. Further, this study also shows that receiving information reduced the likelihood of elite capture of the BLSM fund being levied by local leaders by around 25 percentage points. Households that reported understanding the content of the information provided, received significantly higher benefits, receiving almost their full entitlement of rice. This finding is in accordance with studies by Reinikka and Svensson (2004, 2005), who argued that the provision of information succeeded in increasing household benefits by ensuring that local leaders did not divert the benefits of poverty programs away from their intended beneficiaries.

In the following section we outline the background to the introduction of the KPS as well as the delivery mechanism of the programs. In Section II we present our data and detail our estimation of households' PMT Score that in turn determines their eligability. In Section III we discuss our estimation strategy and present our results, while in Section IV we conclude.

I. Institutional Background

A. Pre-Information Campaign Performance of Targeted Poverty Programs

Since 1997 the Government of Indonesia has implemented several strategies and programs to alleviate poverty (see Tohari et al. 2017). These programs are clustered according to their targeted beneficiaries. Programs targeted at the individual (e.g. Jamkesmas)[6] and household (e.g. Raskin, BLSM, and PKH)[7] levels are classified under the first cluster. Community

[6] Jamkesmas is health insurance for the poor (previously known as *Asuransi Kesehatan untuk Keluarga Miskin*, or Askeskin, later renamed Jamkesmas). In 2014, Jamkesmas covered some 24.7 million households or 96.4 million people.

[7] PKH is a Conditional Cash Transfer program managed by the Indonesian Ministry of Social Affairs that targets the bottom 5% of the population. PKH beneficiaries receive direct cash transfers 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 vaccination completions.

targeted programs (e.g. *PNPM Mandiri*)[8] fall under the second. A third cluster includes programs targeted at micro and small enterprises (e.g. *Kredit Usaha Rakyat* – KUR).[9]

Previous research has identified several program deficiencies. For Raskin these include: (1) Rice not reaching eligible households, i.e. leakage during the delivery process.[10] (2) Evidence of frequent Raskin purchases by poor and non-poor households alike (Banerjee et al. (forthcoming), Olken 2005)[11] and (3) Local governments failing to judiciously allocate the Raskin budget thereby leading poor households having to pay higher prices for rice in addition to delays in rice distribution (Hastuti, Sulaksono and Mawardi 2012).

The BLT program in 2005 and 2008 suffered from similar problems. According to Sumarto et al. (2006) and World Bank (2012a), the problems associated with the BLT implementation include: (1) Significant targeting errors (2) Elite capture through deductions of BLT benefits that increased markedly between 2005 and 2008[12] and (3) Significant time and travel costs associated with the BLT disbursement process via district post offices, which are typically located in the capital district.

To address these shortcomings, the GoI, between 2011 and 2014, made significant changes to both the targeting mechanisms and service deliveries 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 (see Tohari et al. 2017 for detail discussion on the targeting improvement). Following improvements in targeting, in the third quarter of 2013, the GoI also introduced the Social Security Card (*Kartu Perlindungan Social - KPS*).

[8] PNPM Mandiri (for *Program Nasional Pemberdayaan Masyarakat Mandiri* or the National Program for Community Empowerment) is Indonesia's largest community-driven development program to help alleviate poverty through empowering local communities. There are several components of the PNPM Mandiri, two of which are PNPM Rural, that began in 1998 as Kecamatan Development Program (KDP) and PNPM Urban, which begun in 1999 as the Urban Poverty Program (UPP). Interested readers are referred to TNP2K (2015b).

[9] KUR (for *Kredit Usaha Rakyat* or credit for micro and small enterprises) are credit/working capital and/or investment financing schemes for enterprises that are unable to meet certain banking requirements. The amount of credit provided to each enterprise is less than IDR. 5 million (about 500 USD).

[10] Existing administrative records are unable to indicate the point at which the "missing" rice exits the delivery chain since no single authority is responsible from the point of Raskin rice procurement to household purchase (World Bank (2012b).

[11] The amount of Raskin rice purchased by a household is roughly constant across the entire consumption distribution, meaning non-poor households buy as much Raskin as poor, near-poor, or vulnerable households (World Bank, 2012b). In 2010, the World Bank (2012b) estimates that the average amount of Raskin rice bought by poor households was approximately 3.8 kilograms per month.

[12] Deductions from BLT are most commonly made by village or sub-village level officials ostensibly so that BLT funds can be redistributed among non-beneficiaries (the most common reason for deductions) (World Bank, 2012a).

Targeting performance can be evaluated along (i) the extensive margin i.e. whether eligible households take receipt of program benefits and (ii) the intensive margin i.e. whether eligible households take reciept of all the benefits to which they are entitled. In this paper, we focus on the intensive margin. First in relation to the Raskin program, we examine the effects of information provision on the amount of rice received, using data on the number of kilograms of raskin rice purchased by households and the price that they paid. We proceed to evaluate the impact of information provision on BLSM deductions; in other words the impact of information provision on elite capture. Finally, we provide evidence of households' comprehension of the information provided in terms of Raskin and BLSM, on both rice reciept and elite capture.

B. The KPS and the Information Intervention

The KPS card was the first attempt by the GoI to confirm the eligibility status of households. Where possible it was sent directly to households using the postal service. As shown in Appendix Figure B.1., the card contains information on the household head, their spouse and address as well as barcodes representing the family card number, in an effort to protect the card from fraud. Accompanying the KPS card was additional information about how to use the card for accessing the benefits of poverty programs (see Appendix Figure B.2.). Among KPS card recipients, around 16% reported that they did not receive any information whatsoever. 77% reported receiving a complete information package, while 7% stated they had received an information package but that it was incomplete.

C. Delivery Mechanism for Raskin and BLSM Programs

Our outcomes of interest include the benefits received from the Raskin program, which is measured by the number of kilograms of rice purchased through Raskin and the probability of the BLSM fund being levied by local leaders. It is critical to understand the delivery mechanisms for these two programs in 2014, which we address below.

Raskin Program

The Raskin program aims to reduce household expenditure on food, and particularly on rice, the staple food in Indonesia. In 2013 and 2014, the program covered around 15.5 million of the poorest Indonesian households based on UDB and PPLS11. According to the 2014 Raskin Guidelines,[13] the implementation of the program has not changed since its inception. Panel A

[13] Kemenkokesra. (2014). *"Pedoman Umum Raskin 2014"* (General Guideline: Rice Subsidy for Poor People 2014). Jakarta: Kemenkokesra.

of Figure B.3 in the Appendix describes the delivery mechanism for the Raskin program. Since 2011 several agents have been involved in the procurement and delivery of Raskin rice. They include: (i) the Coordinating Minister of Social Affairs (for *Kementerian Koordinator Bidang Kesejahteraan Rakyat* or Coordinating Minister of Social Affairs), later called Kemmenko PMK (for *Menteri Koordinator Bidang Pembangunan Manusia and Kebudayaan* or Coordinating Minister of Human Resources and Culture), and the Vice President's National Team for the Acceleration of the Poverty Reduction (TNP2K), which together determine yearly allocation and price of rice,[14] (ii) the Bulog (the National Logistics Agency) responsible for procuring rice from producers and delivering the rice to over 50,000 distribution points across Indonesia. Raskin beneficiaries are expected to make monthly Raskin purchases from these distribution centres[15] and (iii) the District government that is responsible for the logistics of transporting Raskin rice to recipient households.

We measure the effectiveness of the information intervention using the average amount of Raskin rice bought by the beneficiary household in the last three months. Summary statistics of this outcome variable and characteristics of Raskin beneficiaries are presented in Table A.5. of the Appendix. Although all three programs, Raskin, BLSM, and the KPS should potentially be targetted at the same households (those in the bottom quartile of the population), the number of households that actually received Raskin benefits is almost double the number of BLSM recipients (26,212 for Raskin as opposed to 13,423 for BLSM respectively). Further, among those who bought rice under the Raskin program, only 33.2% held the KPS card, while 27.4% also received the information treatment. The average amount of rice bought by households that received the information is only six kilograms however, which is less than half the intended allocated benefit. Even though this means that the rice received by these targeted households is higher when compared to the average rice bought in 2010, which was only 3.8 kilograms.

BLSM

The BLSM program aims to maintain the purchasing power of targeted households that would otherwise be affected by oil price increases. Similarly to Raskin, the BLSM covers around 15.5

[14] According to the general guidelines of Raskin 2014, the total number and the list of Raskin beneficiaries were obtained from the Unified Database of TNP2K. In terms of benefit, each targeted household should receive 15 kg/month per month of rice. The price of Raskin rice is IDR 1600 /kg at the Sharing Point (*Titik Bagi*).

[15] The distribution centres (or *Titik Distribusi*) of Raskin are mostly located in village offices or other places that are decided upon between Local Government and Bulog. The local government and village administrative apparatuses are then responsible for notifying eligible beneficiaries and arranging the transport of rice from distribution points to households (*Titik Bagi* or sharing points).

million of the poorest households who received cash benefits of about IDR 150 thousand per month for a four-month period.[16] In 2013, BLSM payments were made in June/July and September/October via PT POS Indonesia, the State-owned postal company. In contrast to Raskin that is disbursed monthly. Since the SPS was conducted in the first quarter of 2014, we examine the effect of the information treatment on benefits received under both the BLSM and Raskin programs.

The payment process of the BLSM in 2013 began by delivering the KPS directly to targeted households by PT POS Indonesia. Hastuti et al. (2013), based on a rapid assessment in four municipalities, argue that there was some evidence that PT POS Indonesia used local leaders to deliver the KPS. To access cash payments, beneficiary households are expected to have a KPS card, an authorisation letter and additional supporting documents (e.g. family card or identity card or domicile card).[17] The fund can be accessed by other household members only under special circumstances with evidence of official supporting documents, typically issued by the local leader. This makes it almost impossible for households that did not receive the KPS to access BLSM, except if they received the fund 'unofficially'; for example if local leaders levied the BLSM fund and redistributed benefits to non KPS holder households (World Bank, 2012a).

The BLSM payment processing facilities are located in District Post Offices. In remote areas and those without access to a post office, PT POS Indonesia was expected to visit and open special payment counters. These special counters were based in local leaders' offices. The BLSM program rules are more stringent than those of Raskin and accordingly, households that did not receive the KPS card could not access the BLSM.

We examine the affect of information provision on households' access to the BLSM by comparing the probabilities of levies being imposed by local leaders on the household's allocated BLSM funds, between treated and non-treated households. Summary statistics on BLSM beneficiaries and their characteristics are presented in Table A.6. in the Appendix. Of the total BLSM beneficiaries, around 70% received the information treatment, while the remaining households received the KPS although without the information intervention. The

[16] Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak (2013). *"Buku Pegangan Sosialisasi dan Implementasi Program-Program Kompensasi Kebijakan Penyesuaian Subsidi Bahan Bakar Minyak 2013"* (The guidelines for the implementation of the 2013 compensation program for Fuel Subsidy Reduction Compensation Program). K. W. P. RI. Jakarta: Sekretariat Wakil Presiden.
[17] Domicile Card is issued by local leaders (sub village or village heads) to prove that the individual/household live in the same village.

summary statistics further highlight that treated households are less likely to have their BLSM funds levied by local leaders (16% for those that received the information, as opposed to 20% for those who did not).

II. Data, PMT Score and Eligibility

To evaluate the effect of the information campaign on the benefits received from poverty programs, this study uses several sources of nationally representative data in conjunction with administrative data from the GoI; specifically the PMT coefficients and the official district quotas used by the GoI to select the beneficiary households from the UDB. Below we describe these datasets in addition to the challenges faced and the steps used to merge them.

Data

The data for this study come from the National Socioeconomic Survey (SUSENAS), the Social Protection Survey (SPS) and the Village Potential Census (PODES), and are described in detail below.

The SUSENAS Survey

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, the Central Bureau of Statistics of Indonesia (BPS) changed the survey frequency to quarterly, and for each quarter, the SUSENAS covers some 300,000 individuals and 75,000 households. In this paper, we utilize data from the 2014 wave of the SUSENAS survey to: (i) generate variables that are required to estimate the PMT Score for each household using the official PMT coefficients (ii) obtain control variables that are not included in the PMT score estimation and (iii) construct poverty indicators as outcome variables.

Social Protection Survey (SPS)

The second dataset used in our analysis is the 2014 Social Protection Survey (SPS), which was conducted jointly by the BPS and 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 was only asked in the last two rounds of the survey however. We therefore use data from the first quarter of 2014 since it was the period just after the implementation of the KPS in order to construct our outcome and treatment variables.

Village Census (PODES)

The last source of data are from the 2011 and 2014 waves of the PODES, which provide information on all villages/*desa* in Indonesia. The variables produced using this census include the characteristics of the village, some of which were used in estimating the PMT scores.

Merging the datasets

The greatest challenge in merging the datasets is the fact that since 2011 the BPS has not published the village and subdistrict codes for their household-based surveys. To address this, we proceed in the following way:

i) First, we merge data from Quarter 1 2014 SPS with Quarter 1 2014 SUSENAS. Using the actual household ID that is available in these two datasets, the selected variables from these two datasets are combined. Overall, around 70,336 households of the SPS sample can be identified from the total of 71,051 households in the SUSENAS survey.

ii) These combined data are then merged with the 2014 pooled SUSENAS to obtain village and sub-district IDs using a 'bridging code' shared privately with us by the BPS.[18]

iii) Finally, we merge the resulting dataset with selected variables from the PODES data using a village identifier in order to obtain village-level variables. After merging with the PODES data, we are able to identify 67,118 households including 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, discussed in detail below.

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

Estimating the Household's PMT Score and their eligibility

Measuring PMT scores, thereby defining the eligibility criterion of each household for the KPS, are important steps in providing social protection in Indonesia. Estimating the PMT score involves:

1. Selecting 15.5 million beneficiaries (or 25% of the poorest households) for the KPS using data from the UDB. The UDB contains information on the bottom 40% of the Indonesian population collected through PPLS11 (*Program Pendataan Perlindungan Sosial 2011*) together with their estimated PMT scores. To estimate the PMT score and rank of each household in the UDB, the GoI used coefficients that are measured using SUSENAS and PODES 2011. These coefficients are unique to the 482 districts from the total of Indonesia's 497 districts in 2011.[19] The PMT score for each household is then measured using each household's observable information, which in turn is plugged into the corresponding district coefficient and subsequently ranked. Using household's PMT scores and ranks, the government then selects a list of intended beneficiary households.
2. Using these official PMT coefficients, this study recovers households' PMT scores in 2014: (1) using data from SPS, SUSENAS and PODES in 2014, to construct variables that are comparable to those variables used in PPLS11 (2) following the same steps as conducted by the GoI in which the 2014 variables are plugged into the official PMT coefficients and (3) ranking each household based on their PMT score. As our study uses nationally representative data, the household rank represents their rank relative to the total population. Each household's eligibility for social welfare programs depends upon whether their PMT scores lies above or below their district's cut-off. The cut-off for each district is measured using the official quota used by the GoI to select the list of KPS program beneficiaries that are unique to each district.

[19] For other 15 districts, the GoI implement universal targeting system. For these specific areas, such as several districts which have high incidence of poverty, the GoI selects intended beneficiaries using a 'negative lists' method, which means all households are eligible for poverty programs, except those that contain a public servant, local leaders, high ranking military officials etc.

III. Empirical Estimation

Household's eligibility for social welfare programs is based upon their PMT score relative to their district's cut-off. We investigate the impact of receiving information on the intesive margin of receiving rice under the Raskin program as well as the likelihood of receiving full benefits under the BLSB initiative. Let pmt_i be the PMT score for each household and $\overline{pmt}$ be the PMT cutoff for each district. Then, I, defines the eligibility of each household to receive the information intervention, (TNP2K, 2015a):

$$(1) \qquad I = 1 \text{ if } pmt_i \leq \overline{pmt}, \text{ and}$$
$$I = 0 \text{ if } pmt_i > \overline{pmt}.$$

For each eligible household, we can define their potential outcome, B, with (B_1) if they received the treatment and (B_0) otherwise. Following Rubin (1974), the difference between the average benefit of recipient households relative to non-treated households becomes:

$$(2) \qquad E(B|I=1) - E(B|I=0) = \underbrace{E(B_1 - B_0|I=1)}_{\theta} + \underbrace{E(B_0|I=1) - E(B_0|I=0)}_{\varepsilon}$$

Our estimate of interest is the average treatment-on-the-treated, i.e, the effect of receiving the information treatment, θ, for subgroup of compliers. The main challenge faced in this study is the prospect of ommited variable bias, ε; unobserved determinants that are potentially correlated with the probability of receiving the information and with the level of benefits received.

A. The Impact of Information on the Benefit Received

First we implement a regression discontinuity methodology by exploiting the discontinuity of program eligibility in Equation (1). Our outcome variable is the average amount of Raskin rice bought per month in kilograms following the intervention (R). The average treatment effect in Equation (2) can then be written as:

(3) $\theta_R \equiv E(R_1 - R_0 | I = 1)$

Where θ_R denotes the causal effect of receiving the information treatment. R_1 is the average amount of rice bought by households that received the information, I. R_0 rather refers to the average amount of rice bought by non-treated households.

The empirical challenge in obtaining a consistent estimate of θ_R in Equation (3) is that selection into treatment is endogenous. As shown in Appendix Table A.5. and A.6, households that receive information have different characteristics compared to those households that did not receive the information. For example, on average, they have lower PMT scores, are more likely to also receive the BLSM, are less likely to be living in close proximity to the district office, have access to national TV channels and live in a village with a male leader. Such differences tend to zero however, when we restrict our sample to households close to the cutoff, while the amount of rice bought still changes (discontinuously) at the cutoff.[20] Therefore, comparing households within a sufficiently narrow bandwidth of the cutoff, but on opposite sides of it, identifies the [local average] treatment effect of the information treatment. Figure B.7. in the Appendix depicts the discontinuity of the outcome variable around the cut-off and this is consistent when implementing higher order polynomials.

As previously discussed, the Indonesian Government implemented 482 unique PMT models and cut-offs for each district in Indonesia, of which 471 are used in our analysis. Eleven districts were dropped when we merged our datasets. Since the sample for each district is not representative however, we pool our data and conduct our analysis at the national as opposed to the district level. In order to implement a single cut-off, i.e. discontinuity, we normalize each district's cut-off by subtracting the district's PMT cut-off from the PMT score for each household. Our running variable, S_i, then equals the district cut-off minus the PMT score $s_i \equiv \overline{pmt} - pmt_i$, with cut-off at zero. If s_i is positive, this means that the household should receive the information treatment. If s_i is negative, households should not be receiving the treatment. More formally, let S denote our running variable which represents the district cut-off minus the PMT Score with $S = 0$ at the cut-off. Then, $Z \equiv 1(S \geq 0)$ is a treatment assignment dummy that equals 1 for those households whose PMT score is lower than or equal to the district cut-

[20] Since we only have the PMT score for each household as pre-intervention indicators at the household level, we assume that household-specific variables are represented by their differences in the PMT scores, since households around the cut-off are similar.

off. The causal effect of the information on benefits received from the Raskin program can be estimated for those households around $S = 0$ by considering the ratio between the discontinuity of the outcome and the discontinuity of the probability to be treated at the threshold. Moreover, the ATT in Equation (3) can be shown as:

$$\text{(4)} \qquad \theta_R = \frac{\lim_{S \to 0} E(R \mid S = 0^+) - E(R \mid S = 0^-)}{\lim_{S \to 0} E(I \mid S = 0^+)}$$

Where $S = 0^+$ and $S = 0^-$ denote households that are marginally above and marginally below the cut-off, and the conditional expectation refers to the benefits received under Raskin and the proportion of the households who received the information treatment, I, in these two groups. The fundamental identifying assumption is that Z is as good as randomly assigned within an arbitrarily narrow bandwidth of $S = 0$. This assumption is particularly plausible in this study since the total number of households for each district are selected on the basis of district quotas (TNP2K, 2015a). It implies that there must be a significant number of households just to the right of the cut-off that have PMT scores very close to eligible households that did not receive the treatment.

As a result of the programs' eligibility rules, the probability of receiving the information treatment for households below the threshold, $S = 0$, is zero by definition since they are not eligible for treatment. The targeting of this intervention contains both exclusion and inclusion errors however (Tohari et al., 2017).[21] For example, Table A.3. in the Appendix shows that only 63.97% of total households who received the treatment were eligible households. As such, there is a degree of fuzziness in the application of the eligibility test.[22]

In the presence of measurement errors, the sample analog of (4) is inconsistent for the parameter of interest. Rescaling we can write:

[21] It is well established that the targeting of poverty programs often suffer from errors of inclusion and exclusion. The inclusion error refers to non-eligible households being erroneously included, while exclusion errors occur when some eligible households are erroneously excluded from receiving the program benefits (for further details please refer to Ravallion (2007).

[22] Figure B.6. in the Appendix shows the probability of receiving the information treatment given S and its discontinuity at the cut off.

(5) $$(\theta_R | \, compliers) = \frac{\lim_{S \to 0} E(R \mid S = 0^+) - E(R \mid S = 0^-)}{\lim_{S \to 0} E(I \mid S = 0^+) - E(I \mid S = 0^-)}$$

Assuming monotonicity and conditional on S^*, the process genenerating measurement error is orthogonal to the process of interest. The ratio in (5) is then the Local Average Treatment Effect (LATE) of receiving information on the benefit received from Raskin on the subset of compliers near the cut-off (Imbens and Angrist, 1994, Hahn, Todd and Van der Klaauw, 2001). The causal effect can then be estimated using a simple instrumental variable strategy, where the eligibility status is utilized as an instrument for treatment.

Table 1 presents the results of the 2SLS kernel local linear regressions of the effects of receiving information on the benefits received from the Raskin program. To select the optimal bandwidth, we follow the criteria proposed by Imbens and Kalyanaraman (2012) henceforth, IK2012 in the first three Columns and Calonico, Cattaneo and Titiunik (2014), henceforth, CCT2014, in Columns four to six. The polynomial order, the size of the bandwidth and the observations inside the bandwidth are presented in Table 1.

The 2SLS coefficients using nonparametric estimates without adjusting for covariates, in Columns (1) and (4) in Panel A of Table 1, show that in general, receiving information increases the benefit received from Raskin by about 30.6 percentage points according to IK2012, and 39.2 percentage points according to CCT2014. We also test whether the treatments differed between Java and Non-Java, by splitting the sample. Java is the most populous island in Indonesia and previous studies (e.g., Ravallion and Dearden (1988)) have shown that Java tends to be more egalitarian whereby benefits are moreoften shared. Given this, the distribution of the benefits received from poverty programs could differ between Java and other areas of the country. The results using linear order polynomials in Panel A of Table 1, as presented in Columns (2) and (3) based on IK2012 and Columns (5) and (6) based on CCT2014, show that there is significant difference in the impact of information between Java and other provinces, even though the effects are not statistically significant using lower order of polynomials. When we implement cubic order polynomials, the results in both Java and Non-Java become statistically significant. Under this specification, the effect of information on the Java subsample is about 61.1 percentage points higher and statistically significant, while the effects in the Non-Javan provinces are about 32.8 percentage points under IK bandwidths. Our estimates using higher order polynomials, except cubic order polynomials under the CCT bandwidth selection, are likely generating higher estimates because higher order polynomials assign far greater weights to observations further away from the discontinuity (Gelman and Imbens, 2017).

Table 1 The Effect of Receiving Information on Log (Raskin Bought) using RD Estimation

	Bandwith: IK (2012)			Bandwith: CCT (2014b)		
	All	Java	Non Java	All	Java	Non Java
	(1)	(2)	(3)	(4)	(5)	(6)
E (*R* | Information = *0*) (Kg)	4.738	4.178	5.263	4.738	4.178	5.263
Panel A: Effect of Information without Covariates-Adjusted						
Linear	0.306	0.542	0.170	0.392	0.522	0.266
	(0.146)**	(0.445)	(0.156)	(0.131)***	(0.386)	(0.144)*
Quadratic	0.416	0.539	0.290	0.447	0.595	0.315
	(0.130)***	(0.385)	(0.142)**	(0.126)***	(0.341)*	(0.134)**
Cubic	0.457	0.611	0.328	0.402	0.759	0.243
	(0.128)***	(0.334)*	(0.137)**	(0.133)***	(0.356)**	(0.140)*
Size of bandwidth [L: R]	[0.178 : 198]	[0.168 : 0.341]	[0.196 : 0.198]	[0.115 : 0.128]	[0.125 : 0.229]	[0.129 : 0.131]
Observations inside bandwidth	8,483	6,219	4,731	5,573	4,111	3,229
Observations	26,083	12,302	13,781	26,083	12,302	13,781
Panel B: Effect of Information with Covariates-Adjusted						
Linear	0.259	0.568	0.140	0.350	0.503	0.225
	(0.148)*	(0.489)	(0.156)	(0.132)***	(0.455)	(0.145)
Quadratic	0.381	0.513	0.255	0.410	0.495	0.270
	(0.132)***	(0.437)	(0.142)*	(0.127)***	(0.388)	(0.136)**
Cubic	0.428	0.521	0.294	0.371	0.689	0.204
	(0.129)***	(0.404)	(0.139)**	(0.135)***	(0.394)*	(0.143)
Size of bandwidth [L: R]	[0.180 : 0.193]	[0.192 : 0.419]	[0.202 : 0.193]	[0.116 : 0.124]	[0.129 : 0.281]	[0.131 : 0.127]
Observations inside bandwidth	8,322	7,435	4,676	5,496	4,971	3,174
Observations	26,083	12,302	13,781	26,083	12,302	13,781

This table displays nonparametric estimates of the effect of receiving information on the benefit received from the Raskin Program. The outcome variable is the log average Raskin rice bought in the last three months. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cutoff. *E (R | Z = 0)* denotes the average monthly of Raskin Rice bought in the last three month by households who are not eligible for the KPS program (*Z=0*). The table reports the bandwidth selection rule, IK2012 or CCT2014, the size of the bandwidth (distance from zero) and the number of observations included in the bandwidth. The standard errors (presented in parentheses) are clustered by the village. ***(**)* represent 1(5)10% significance level.

We also include pre-intervention covariates related to village and head of village characteristics following Frolich (2007) and Calonico et. al. (2016).[23] Imbens and Kalyanaraman (2012) however, note that the inclusion of additional covariates should not affect such analyses significantly. The results are presented in panel B of Table 1, which shows that in general the inclusion of covariates produces slightly lower estimates. For example, using linear order

[23] Pre-intervention covariates related to village and head of village are derived from 2011 PODES data.

polynomials and the IK bandwidth selection, the covariates-adjusted estimates of providing information on Raskin are about 25.9 percentage points higher, while under non-adjusted covariates estimation it is about 30.9 percentage points.

Interestingly the covariates-adjusted RDD estimation under IK2012 bandwidth selection and linear order polynomial produces the closest estimate when compared to the results of Banerjee et al. (forthcoming). Those authors find that providing information through the Raskin card increases the rice subsidy received by about 26% when compared to the control group. It can be argued that our research provides external validity of Banerjee et al. results therefore.

B. Robustness Checks and Extensions

Sensitivity Tests

First, we choose a range of placebo cut-offs to ensure that the discontinuity of the outcome of interest only occurs at the true cut-off. Table 2 summarizes the estimate of the effect of information for selected cut-offs ranging from -0.1 to 0.1 in increments of 0.05. Figure 1 plots the estimates. The cut-off at 0 is included as a benchmark. As expected, with the exception of 0 i.e the true cut-off, the information treatment did not change at any other placebo cut-offs. In terms of magnitude, the effect of information is smaller compared to the true effects at all other cut-offs. This implies that the outcome of interest does not jump discontinuously at any other cut-off other than at 0.

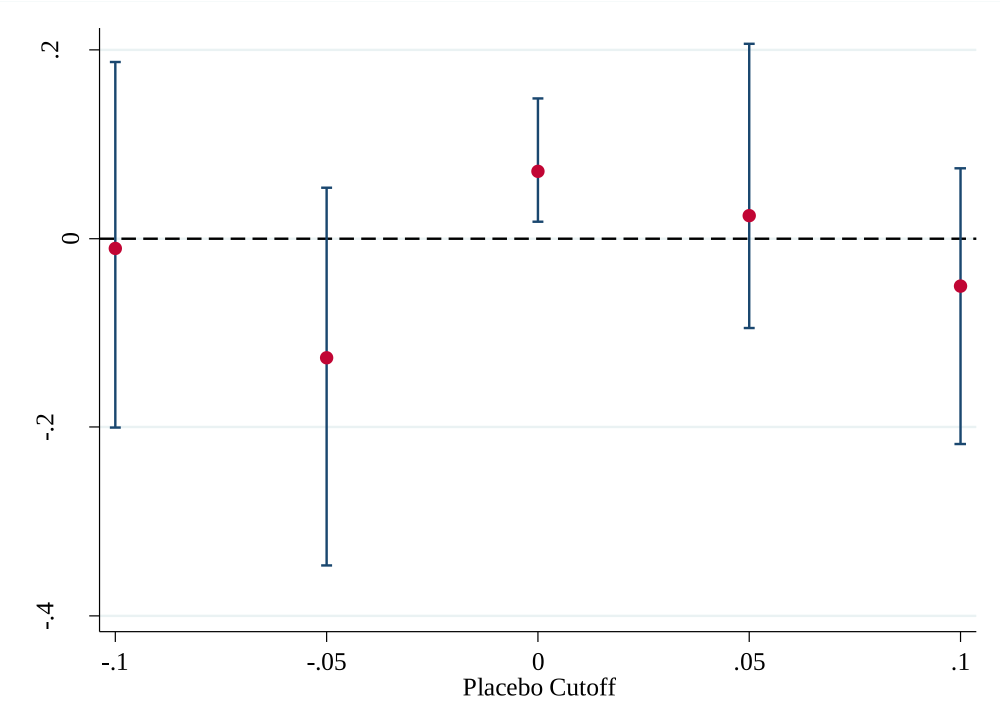
In choosing a bandwidth, it is critical to consider an optimal balance between estimation precision and estimation bias (Lee and Lemieux 2010). Larger bandwidths, on the one hand, yield more precise estimates since more observations can be relied upon in estimation (i.e. greater efficiency). On the other hand, when a larger bandwidth is used, resulting estimates are less likely to be accurate as increasingly observations are considered that are located further from the threshold (i.e. greater bias). Figure 2 plots the estimated 2SLS coefficients of the effect of information and the associated confidence intervals for different bandwidth selections or window lengths using IK2012. The area within the vertical dashed lines represents the location of the true optimal bandwidths that are selected based on both IK2012 and CCT2014. Evidentally, as the bandwidth increases, the bias of the estimator increases as its variance decreases. Therefore, it is natural in such a set-up that the larger the bandwidth, the smaller the confidence intervals, but due to bias, the effects will also be displaced.

Table 2 Kernel Local Linear Estimation at selected cut-offs

Alternative Cutoff	Optimal Bandwidth: IK2012	Effect of Information	Robust Inference		Observation	
			P-value	*CI*	Left	Right
(1)	(2)	(3)	(4)	(5)	(6)	
-0.1	0.035	-0.010	0.947	[-0.200 : 0.187]	485	513
-0.05	0.026	-0.126	0.152	[-0.346 : 0.054]	444	460
0	0.177	0.071	0.013	[0.018 : 0.148]	2,670	5,106
0.05	0.037	0.024	0.470	[-0.095 : 0.260]	940	962
0.1	0.035	-0.050	0.335	[-0.218 : 0.074]	956	1,009

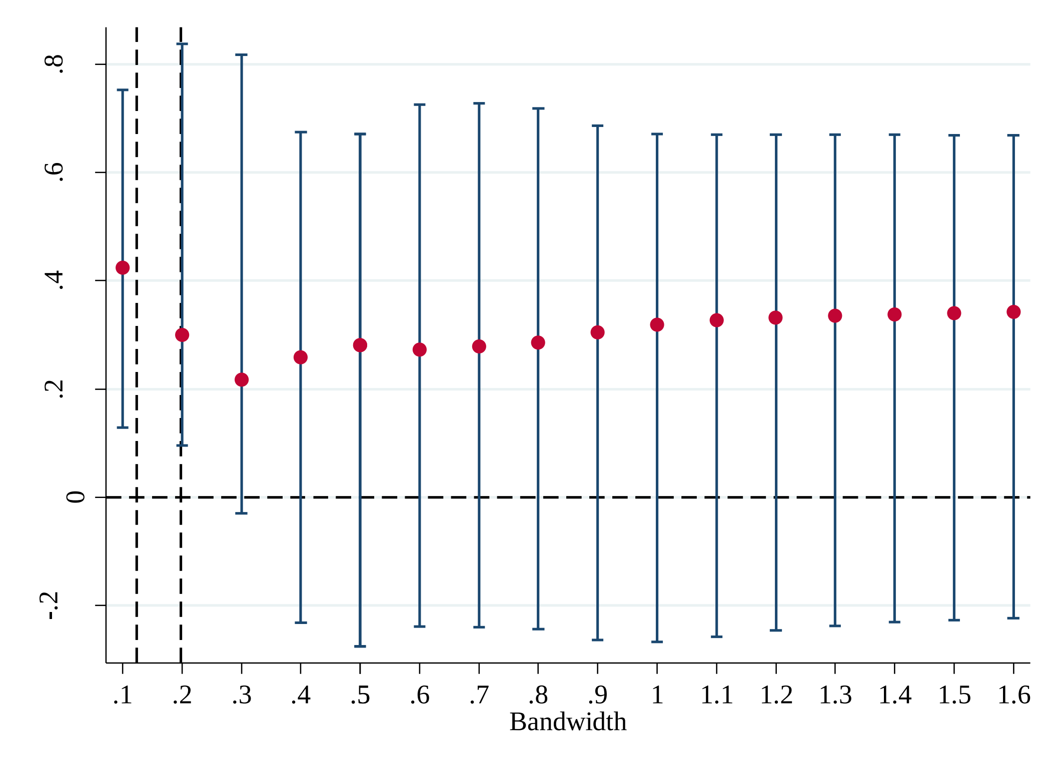
This table displays nonparametric estimates of the effect of receiving information on the benefit received from the Raskin Program at several different cut-offs. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cutoff. Optimal bandwidths are selected using IK2012. Robust *P-value* and *Confidence Interval* are reported in Column 4 and 5, respectively. ***(**)* represent 1(5)10% significance levels.

Figure 1 Sensitivity Analysis on Selected Cut-offs – All sample



This figure presents the sensitivity tests of the effect of information using different placebo cut-offs. The true cut-off, 0, is used as a benchmark for other artificial cut-offs. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cut-off. Optimal bandwidths are selected using IK2012.

Figure 2 Sensitivity Analysis on Selected Bandwidths – All sample



This figure presents the sensitivity tests of the effect of information using different placebo bandwidth. Within the vertical dashed denotes the area in which optimal bandwidths are selected using IK2012 and CCT2014. All coefficients are estimated using a kernel local linear regression and blue lines represent the confidence intervals.

Comparing RD, LATE and LARF

The results from the local kernel regression results confirm that receiving information significantly increases the benefits received from the Raskin program. Below we examine whether the effects are also consistent if they are estimated following Angrist, Imbens and Rubin's (1996) parametric estimate and Abadie (2003) semiparametric approach.[24] Our parametric approach, the estimation of the LATE, implements an instrumental variable technique with eligibility status of the household used as our instrument for treatment. Our semiparametric approach as detailed in Abadie (2003), instead proposes to use a Local Average Response Function (LARF) that allows one to compare the characteristics of treated and non-treated individuals within the compliers' subset, in the absence of knowledge as to who is and is not a complier. The estimation of the LARF is conducted in two steps which are: (1) to

[24] Lee and Lemieux (2010) note a number of alternative estimation strategies and suggest that no single method be relied upon. Our parametric and semiparametric estimations are therefore included to complement our non-parametric approach.

measure the weights, w, by estimating parametrically (or non-parametrically) $p(Z = 1 \mid X)$ and (2) estimating the effects using Weighted Least Square (WLS) with weights equal to w.

With regards national level effects, Columns (2) and (5) in Table 3, show the results from both our parametric and semiparametric estimators, which are slightly different and statistically significant. The magnitude of the effects and their signs show that the provision of information increases the benefits received from the Raskin program by about 37.1 percentage points in parametric and 48.5 in semiparametric estimations, respectively. The result of parametric estimation is in the range of the estimated effects from our nonparametric approach in Table 1, while the result of semiparametric estimation is slightly higher in all nonparametric alternative estimations.

Table 3 The Effect of Receiving Information on Raskin Intensive margins using LATE and LARF Estimations

		LATE			LARF		
	OLS	All Sample	Java	Non- Java	All Sample	Java	Non- Java
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reduced form		0.184	0.192	0.181			
		(0.003)***	(0.006)***	(0.004)***			
Effect of Information	0.215	0.371	0.426	0.368	0.485	0.465	0.426
	(0.012)***	(0.043)***	(0.066)***	(0.057)***	(0.068)***	(0.142)***	(0.080)***
First Stage Coef. of Z		0.226	0.217	0.238			
		(0.006)***	(0.009)***	(0.009)***			
First Stage *F-Stat* of Z		1239.46	598.1	687.95			
Control Village	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Vill. Head	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,212	26,212	12,302	13,910	8,011	3,285	4,726

This table shows the estimates of the effect of receiving information on the benefit received from the Raskin Program. Dependent variables are the log average Raskin rice bought in the last three months. Column (1) is the estimation result using OLS estimation, ignoring the endogeneity on selection. The first stage instrument denotes a dummy $Z = 1$ if households are eligible, the first stage coefficient of Z and the F-statistic (for the excluded instrument which is adjusted for heteroskedastic and clustered standard errors) are also reported in Column (2) – (4). Column (2)-(4) is the LATE estimation result following Angrist, Imbens, and Rubin (1996). Column (5)-(7) is the LARF result following Abadie (2003). All standard errors are clustered at the village level and computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron, Gelbach and Miller, 2008). ***(**)* represent 1(5)10% significant level.

The difference in the effect of the information treatment between Java and Non-Java is noteworthy. In general, our parametric and semiparametric estimates produce consistent results with the nonparametric estimation in which the effect of information on social benefits away from Java is lower than in Java itself and all the results are statistically significant. In terms of the magnitude however, using our parametric results in Columns (3) and (4) of Table 3, we observe that the provision of information increases the benefits received from the Raskin program by about 42.6 percentage points in Java households and by 36.8 percentage points in Non-Java households, respectively. Moreover, our semiparametric results for Java and Non-Java households, produce the same results with small difference between Java and Non-Java compared to our parametric results.

Finally, it is also important to note that the OLS estimate in Column (1) of Table 3 is downwardly biased. According to the OLS result, the increase in the benefits received from Raskin is about 21.5 percentage points conditional on covariates. The estimated effect of information increases when we instrument this variable with the household's eligibility to receive treatment however. Overall therefore, we can conclude that the provision of information to eligible households increases the level of benefits received by between 30-40 percentage points on average.

C. How did Information Affect the Benefit Received?

Next we examine the mechanism through which information interventions may influence program recipients. Kosack and Fung (2014) drawing upon evidence from 16 experimental evaluations explain the manner in which the provision of information could improve public services. They hypothesise that information can be useful for improving program governance via: (1) the action cycle (2) the short and long routes of accountability and (3) the willingness of providers, policymakers, and politicians to make improvements.

Two possible arguments can be used to explain the effect of information when the government is a monopoly service provider. The first is that the provision of information could improve the awareness of individual's rights among potential beneficiaries, which in turn could lead to more proactive participation by the public in monitoring program delivery. This is shown by Pandey et al. (2009) in India. Secondly, additional information could increase the bargaining position of the beneficiaries in their dealings with the local leader, as shown by Banerjee et al. (forthcoming) for Indonesia. Fox (2007) however argues that information can only improve public participation and increase benefits if the information is understandable and actionable.

Another possible argument is that information could reduce the probability of local leaders capturing program benefits, i.e. elite capture. This argument has been supported by (Reinikka and Svensson, 2004, 2005) using evidence from Uganda. They show that the provision of information to both schools and parents helped to monitor local officials handling education funds and was highly successful in reducing elite capture, while also having a positive impact on education outcomes. Local capture and corruption in the Indonesian context has been studied by Suryadarma and Yamauchi (2013) who investigated missing funds in *Inpres Desa Tertinggal* (IDT) program.[25] Olken (2007) found that increasing top-down monitoring or central government audits reduced missing funds from the Indonesian village project.

In this study, while corroborating the external validity of Banerjee et. al. (forthcoming), we are unable to test their proposed mechanism through which information empowers poor households; since suitable questions were not posed in the SPS. Rather, following Reinikka and Svensson (2004, 2006), Olken (2006) and Suryadarma and Yamauchi (2013), we investigate an alternative channel, that of reducing elite capture. We hypothesise that information provision influences the benefits received via reducing the likelihood of local elites capturing poverty program benefits. In order to test this hypothesis, our proxy measure of local capture is an indicator variable, which takes the value 1 if the recipient household had a levy imposed by local leaders or not, (L).[26] The average treatment on the treated from Equation 2 can be rewritten as:

$$(6) \qquad \theta_L \equiv E(L_1 - L_0 | I = 1)$$

Where θ_L denotes the causal effect of receiving the information, L_1 refers to the probability of a levy being imposed on the BLSM fund by the local leader given the household received the information and L_0 the probability of the fund being levied for those households who did not receive the information treatment.

[25] *Inpres Desa Tertinggal* (IDT, Presidential aid for poor villages) was a village targeted poverty program implemented by the GoI in the period of 1990s. Under this program, selected villages were assigned to choose poor households that would be eligible for IDT loans based on village-level meetings that were facilitated by the village head and a local government agency called *Lembaga Ketahanan Masyarakat Desa* (LKMD, Village Community Resilience Board). The selected households were formed into community groups (*pokmas*,or kelompok masyarakat). These *pokmas* leaders were also responsible for managing loan activities within their groups (Suryadarma and Yamauchi 2013).

[26] Our proxy follows the logic behind the definition of local capture used by Reinikka and Svensson (2005). They used the proportions of intended and actual funds received as a proxy for local capture. It is also consistent with Alatas et al. (2013) whom argue that capture by formal elites occurs during the distribution of benefits and not during the processes when the beneficiary lists are determined by central government.

In estimating (6), it is important to take into account the following considerations. The first is that households need to bring the KPS card with supporting documents to access benefits from BLSM. It is unlikely (if not impossible) for households without KPS to receive any benefits directly from the Post Office. Taking this into account, the usage of eligibility rules as an instrument for information treatment is no longer valid. The most plausible explanation for why households do not receive the package completely include: (1) geographical difficulties (such as the distance between the village and the post office), such that the postman is unable to send the package directly or (2) as a consequence of the first condition, the postman usually uses the help of local village leader to deliver the package. At this stage, local leaders potentially have the opportunity to take the package or information, such that households fail to receive the entire package. To reduce the selection bias into treatment therefore we use whether the household received the package from a postman as an instrument.

Given that the dependent variable in Equation (6) is binary, Angrist (2001) suggests that simple IV models such as those based on Abadie (2003) can be implemented to estimate average effects in a non-linear model with covariates. In addition to Abadie (2003), this study also corrects the selection bias for a non-linear model using a Heckman selection model as well as a simple bivariate probit model (Heckman, 1978). Columns (1) and (2) in Table 4 report the results from using simple OLS and probit ignoring the endogeneity problem of receiving the information.[27] The estimates show that receiving information is associated with a statistically significant decrease of 5 percentage points in the probability of a levy being imposed by local leaders on the BLSM. The estimated effect of receiving information decreases significantly when we correct for selection bias by instrumenting this variable with a dummy variable that equals 1 if households receive the package directly from the postman and 0 otherwise. Column (4) uses the methodology proposed by Abadie (2003). The effect of receiving information on the probability of local capture is further reduced (by 26.7 percentage points), while remaining statistically significant. Similarly in Columns (5) and (6), which implement the Bivariate probit and Heckman two-stage estimators respectively, the effect of receiving information is approximately the same and statistically significant.

Despite receiving information, households' understanding of the content of information campaigns proves crucial in reducing elite capture. This finding complements Banerjee et al.

[27] The endogeneity in receiving treatment among the KPS beneficiaries could be caused, for example, by the local leader sorting the information materials with the objective of preventing households knowing their rights. As shown in Table A.5. and Table A.6. in the Appendix, the percentage of households that receive information is higher when they receive the package directly from postmen.

(forthcoming) whom find that information campaigns increase community awareness and empower citizens to more effectively demand their rights. According to the SPS, about 18% of households that receive information understand the content. [28] We further hypothesise that the status quo, one characterised by incomplete information, is potentially due to local leaders wanting to maintain control of the delivery of poverty programs. Alatas et al. (2013) similarly find that formal elites are more likely to be beneficiaries from the Jamkesmas and Raskin programs, which could be an indication of rent-seeking behaviour.

Table 4: The Effect of Receiving Information on Local Capture of BLSM Fund

	OLS	Probit	Endogenous treatment			
				LARF	Biprobit	Heckman
	(1)	(2)	(3)	(4)	(5)	(6)
Effect of Information	-0.053 (0.017)***	-0.051 (0.017)***		-0.267 (0.037)***	-0.258 (0.059)***	-0.253 (0.087)***
First Stage Coef. of Z			0.075 (0.013)***			
First Stage *F-Stat* of Z			35.94			
Control distance to Post	Yes	Yes	Yes	Yes	Yes	Yes
Control Village	Yes	Yes	Yes	Yes	Yes	Yes
Control Vill. Head	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,324	11,324	11,324	9,536	11,324	11,324

This table shows the estimates of the effect of receiving information on the probability of households receiving BLSM funds without levied. The independent variable is 1 if the BLSM fund was levied by local leaders and 0 otherwise. Columns (1) – (2) display the estimation results using simple OLS and Probit estimations thereby ignoring the endogeneity problem. The first stage coefficient denotes a dummy Z = 1 if households received the package directly from Postman and the F-statistic for the excluded instrument (adjusted for heteroskedastic and clustered standard errors) are also reported in Column (3). Columns (4)-(6) present the estimation results that include endogeneity treatment using Abadie (2003), bivariate probit and Heckman two-stage respectively. The standard errors (presented in parentheses) are clustered at the village and in Columns (4) – (6) computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron, Gelbach and Miller, 2008). ***(**)* represent 1(5)10% significance levels.

D. Implications of households understanding the content of information campaign

To test if understanding the contents of information campaign affects the intensive margin of programs, we estimate a simple Heckman selection model. The outcome variables are similar

[28] Appendix Table A.4. reports the percentage of households whether they understood about the content of information or did not. The understanding of the household is measured based on a question in SPS which clarify how many of the program should be received by the KPS holders. Based on the KPS guideline, number of the programs should be at least 4.

to Equations (4) and (6) in understanding whether households understood the content of the campaign.

Table 5 the Effect of Understanding on Raskin Benefit and BLSM Fund Deduction

	Panel A: Raskin		Panel B: BLSM	
	Selection	Outcome	Selection	Outcome
	(1)	(2)	(3)	(4)
Information	0.283		0.128	
	(0.021)***		(0.031)***	
Village has access to TV Station	0.151		0.331	
	(0.068)**		(0.095)***	
Effect of Understanding		2.780		-0.864
		(0.222)***		(0.241)***
E (Y | Understanding = *0)*		[5.003]		[0.178]
Province Dummy	No	Yes	No	No
Control Village	Yes	Yes	Yes	Yes
Control Vill. Head	Yes	Yes	Yes	Yes
Control Eligibility	Yes	Yes	Yes	Yes
Observations		26,212		13,242
Wald X^2		1,325.36		416.21
Prob > X^2		0.000		0.000

This table shows the estimates of the effect of understanding information using Heckman selection models. The dependent variable in the selection models, in Column (1) and (3), is a dummy variable that equals 1 if households understood the content of the information campaign. The dependent variable in the outcome equation is the log average Raskin rice bought in the last three months in Panel A, while in the panel B is a dummy variable that equals 1 if the BLSM fund was levied by local leaders and 0 otherwise. The outcome equation includes the same variables as the selection equation, except for a dummy variable that equals 1 if households received the information and 0 otherwise and a dummy variable equal to 1 if a village has an access to TV stations or 0 otherwise; and with province dummy variables in Raskin outcome. Estimations are conducted using two-step consistent estimators. The standard errors (presented in parentheses) are computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron et al., 2008). ***(**)* represent 1(5)10% significance levels.

Table 5 presents the results of estimating Heckman selection models, where Panel A presents estimates using the log of kgs of Raskin rice purchased as the dependent variable, while in Panel B we present estimates as to whether a levy was imposed on the BLSM fund. The estimated equations used to generate the results in Columns (2) and (4) include the same variables as the selection equation, except for a dummy variable that takes the value of 1 if the household received the information, and a dummy equal to 1 if the household live in a village with access to TV stations. The use of these variables is similar to an approach that uses those two variables as instruments. The results from our selection models show that those households that receive information are more likely to have a better understanding of the program benefits compared to non-treated households. Those households that understood the content of the information campaign received on average a 278 percentage point increase in the amount of Raskin rice, equivalent to almost the full amount of the intended benefit (13.9 of total benefit 15 kg/month/household). Similarly, in the case of the BLSM, as presented in Column (4), those who understood the information content are more likely to receive the full amount of the BLSM fund.

IV. Conclusion

Information campaigns have been proffered as low cost interventions to improve take-up rates of poverty programs' in developing countries. We contribute to the limited evidence base on the effectiveness of information interventions. In 2013, the Indonesian Government implemented one of the largest targeted information interventions in history, covering about 15.5 million households. To our knowledge, the effectiveness of this campaign on take up of benefits by eligible households has not been rigorously investigated at the national level.

In this paper we contribute to the literature by (i) investigating the extent to which households receive an information campaign and (ii) whether this in turn led to an improvement in the level of benefits. Our results show that the information campaign contributed positively to the benefits received from the Raskin program. However, it should be noted that eligible beneficiaries still received less than their allocated amount. One possible explanation is that local implementers, village leaders, still have authority to distribute the Raskin rice and they may allocate it to both poor and non-poor households.

Further, we investigate a potential mechanism through which information influences the level of benefits received. Our analysis shows that when eligible beneficiaries understand the content of the information campaign, it significantly reduces the possibility of local leaders imposing a levy on the BLSM fund. We speculate that this is because the campaign material included information on the grievance mechanism, advising households to report directly to the central government in case village heads captured the benefit. The complaint resolution puts pressure on local leaders to comply with program rules. Another important finding from our study is that understanding the content of the information campaign improves the likelihood of a household receiving their allocated amount of rice in full. This suggests that the information based intervention should be mindful as to whether their message is understandable and accessible to their beneficiaries. This is clearly challenging for policy makers in developing countries, particularly in Indonesia.

References

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics, 113*(2), 231-263.

Akerlof, G. A. (1970). The market for" lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 488-500.

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., Purnamasari, R., & Wai-Poi, M. (2013). *Does elite capture matter? Local elites and targeted welfare programs in Indonesia*. Retrieved from

Angrist, J. D. (2001). Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice. *Journal of Business & Economic Statistics, 19*(1), 2-28.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American statistical Association, 91*(434), 444-455.

Banerjee, A., Banerji, R., Duflo, E., Glennerster, R., & Khemani, S. (2010). Pitfalls of participatory programs: Evidence from a randomized evaluation in education in India. *American Economic Journal: Economic Policy, 2*(1), 1-30.

Banerjee, A., Hanna, R., Kyle, J., Olken, B. A., & Sumarto, S. (Forthcoming). Tangible Information and Citizen Empowerment: Identification Cards and Food Subsidy Programs in Indonesia. *Journal of Political Economy*.

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression- discontinuity designs. *Econometrica, 82*(6), 2295-2326.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik. 2016. Regression discontinuity designs using covariates. *Working Paper, University of Michigan.*

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics, 90*(3), 414-427.

Cameron, L., & Shah, M. (2013). Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. *Economic Development and Cultural Change, 62*(2), 381-415.

Fox, J. (2007). The uncertain relationship between transparency and accountability. *Development in practice, 17*(4-5), 663-671.

Frolich, M. (2007). Regression Discontinuity Design with Covariates. *IZA Discussion Paper No. 3024, Bonn.*

Gelman, A., & Imbens, G. (2017a). Why high-order polynomials should not be used in regression discontinuity designs. Journal of Business & Economic Statistics, 0-0. doi:10.1080/07350015.2017.1366909

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression- discontinuity design. *Econometrica, 69*(1), 201-209.

Hastuti, Sulaksono, B., & Mawardi, S. (2012). Tinjauan Efektivitas Pelaksanaan Raskin dalam Mencapai Enam Tepat. *Smeru Working Paper*.

Hastuti, S. U., Sulaksono, B., Mawardi, S., & Syukri, M. (2013). *Pemantauan Cepat Pelaksanaan Penyaluran Bantuan Langsung Sementara Masyarakat (BLSM)*. Retrieved from

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica, 46*(4), 931-959. doi:10.2307/1909757

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies, 79*(3), 933-959.

Imbens, G. W., & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica, 62*(2), 467-475. doi:10.2307/2951620

Kosack, S., & Fung, A. (2014). Does transparency improve governance? *Annual Review of Political Science, 17*, 65-87.

Lee, D., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. Journal of Economic Literature, 48(2), 281-355.

Lieberman, E. S., Posner, D. N., & Tsai, L. L. (2014). Does information lead to more active citizenship? Evidence from an education intervention in rural Kenya. *World Development, 60*, 69-83.

Olken, B. A. (2005). Revealed community equivalence scales. *Journal of Public Economics, 89*(2), 545-566.

Olken, B. A. (2007). Monitoring corruption: evidence from a field experiment in Indonesia. *Journal of Political Economy, 115*(2), 200-249.
Pandey, P., Goyal, S., & Sundararaman, V. (2009). Community participation in public schools: impact of information campaigns in three Indian states. *Education Economics, 17*(3), 355-375.
Pradhan, M., Suryadarma, D., Beatty, A., Wong, M., Gaduh, A., Alisjahbana, A., & Artha, R. P. (2014). Improving educational quality through enhancing community participation: Results from a randomized field experiment in Indonesia. *American Economic Journal: Applied Economics*, 105-126.
Ravallion, M. (2007). Evaluating anti-poverty programs. *Handbook of development economics, 4*, 3787-3846.
Ravallion, M., & Dearden, L. (1988). Social security in a" moral economy": An empirical analysis for Java. *The Review of Economics and Statistics*, 36-44.
Ravallion, M., Van de Walle, D. P., Dutta, P., & Murgai, R. (2013). Testing information constraints on India's largest antipoverty program. *World Bank policy research working paper*(6598).
Reinikka, R., & Svensson, J. (2004). Local Capture: Evidence from a Central Government Transfer Program in Uganda. *The Quarterly Journal of Economics, 119*(2), 679-705.
Reinikka, R., & Svensson, J. (2005). Fighting Corruption to Improve Schooling: Evidence from a Newspaper Campaign in Uganda. *Journal of the European Economic Association, 3*(2/3), 259-267.
Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology, 66*(5), 688.
Stigler, G. J. (1961). The economics of information. *Journal of Political Economy, 69*(3), 213-225.
Sumarto, S., Toyamah, N., Usman, S., Sulaksono, B., Budiyati, S., Widyanti, W. D., . . . Sodo, R. J. (2006). *A rapid appraisal of the implementation of the 2005 direct cash transfer program in indonesia: A case study in five kabupaten/kota*. Retrieved from
Suryadarma, D., & Yamauchi, C. (2013). Missing public funds and targeting performance: Evidence from an anti-poverty transfer program in Indonesia. *Journal of Development Economics, 103*, 62-76. doi:http://dx.doi.org/10.1016/j.jdeveco.2013.01.007.
TNP2K. (2015a). *Indonesia's Unified Database for Social Protection Programmes - Management Standard*. Jakarta: The Office of the Vice President of the Republic of Indonesia.
TNP2K. (2015b). *Integrating Community-Driven Development Principles into Policy: From PNPM Mandiri to the Village Law*. Jakarta: The Office of the Vice President of the Republic of Indonesia.
Tohari, A., Parsons, C., & Rammohan, A. (2017). *Targeting Poverty under Complementarities: Evidence from Indonesia's Unified Targeting System*. Retrieved from
World Bank. (2004). *World Development Report 2004: Making Services Work for Poor People*. Washington, DC.
World Bank. (2012a). *BLT Temporary Unconditional Cash Transfer. Social assistance program and public expenditure review 2*. Washington, DC: World Bank.
World Bank. (2012b). *Raskin subsidized rice delivery. Social assistance program and public expenditure review 3*. Washington, DC: World Bank.

Appendices

Table A.1. Proportion of the Sample based on whether they received the KPS

Did you receive KPS card?	Freq.	Percent	Cum.
No	53,167	80.23	80.23
Yes	13,100	19.77	100
Total	66,267	100	

Table A.2. Proportion of KPS holders according to whether they received information

Did you receive information in the KPS package?	Freq.	Percent	Cum.
Yes, complete	10,065	76.83	76.83
Yes, but not complete	941	7.18	84.02
No	2,094	15.98	100
Total	13,100	100	

Table A.3. Proportion of the Sample based on their treatment and eligibility

			Eligible		Households
			Yes	No	
Information	Yes	*n*	9,929	1,077	11,006
		%	90.21	9.79	100
	No	*n*	32,911	23,055	55,966
		%	58.81	41.19	100
Households			42,840	24,132	66,972
		%	63.97	36.03	100

This table presents the numbers and proportions of households that received information conditional on their eligibility. The eligibility rule is based upon whether households' PMT score is above or below its district cut-off. Eligibility rule equals 1 if the PMT Score is less than its distric cut-off and 0 otherwise.

Table A.4. The Characteristics of KPS beneficiaries on responding the information delivered

Whether HHDs receive Information in the envelope	Does HHD understand the benefit of the KPS?				
	No	%	Yes	%	Total
Yes, and Complete	8,271	0.822	1,794	0.178	10,065
Yes, but not complete	801	0.851	140	0.149	941
No	1,763	0.842	331	0.158	2,094
Total	10,835	0.827	2,265	0.173	13,100

Source: Social Protection Survey, Author's calculation.

Table A.5. Outcome Variable and household's characteristics Between Treatment and Control Groups of Raskin Beneficiaries

	Did Households receive information?				Difference	
	No		Yes			
	1	2	3	4	5	6
Monthly Raskin Bought (Kg)	4.738	(3.215)	6.012	(3.799)	1.274***	[0.079]
Receive BLSM	0.145	(0.352)	0.969	(0.174)	0.824***	[0.005]
PMT Score	13.462	(0.343)	13.298	(0.317)	-0.164***	[0.006]
Village Characteristics						
Ln Distance to Nearest District office	2.914	(1.159)	2.818	(1.187)	-0.089***	[0.026]
Ln Distance to Post office	1.651	(1.235)	1.642	(1.209)	-0.010	[0.029]
Availability of Asphalt Road in the village	0.752	(0.432)	0.760	(0.427)	0.008	[0.010]
Road can be accessed for a car	0.928	(0.258)	0.931	(0.254)	0.002	[0.007]
Cultural Mono	0.774	(0.418)	0.773	(0.419)	-0.001	[0.009]
Availability Access to the National TV Station	0.642	(0.479)	0.614	(0.487)	-0.028***	[0.011]
Local Leader Directly Elected	0.840	(0.367)	0.810	(0.393)	-0.030***	[0.008]
Sea Transport	0.037	(0.188)	0.034	(0.182)	-0.003	[0.004]
Padi as main Agriculture Product	0.490	(0.500)	0.500	(0.500)	0.009	[0.011]
Slum Area	0.094	(0.292)	0.093	(0.291)	-0.001	[0.006]
Head of Village Characteristics						
Male	0.933	(0.250)	0.922	(0.268)	-0.011*	[0.006]
Age	44.437	(9.334)	44.173	(9.430)	-0.264	[0.204]
Education:						
No Education	0.013	(0.114)	0.010	(0.098)	-0.003	[0.003]
Primary	0.017	(0.131)	0.013	(0.111)	-0.005*	[0.003]
Junior High	0.137	(0.344)	0.131	(0.338)	-0.006	[0.008]
Senior High	0.526	(0.499)	0.522	(0.500)	-0.004	[0.011]
University	0.045	(0.206)	0.048	(0.214)	0.004	[0.004]
Head of Household Characteristics						
Widow	0.151	(0.358)	0.151	(0.358)	-0.000	[0.005]
Age	49.389	(13.892)	49.796	(13.547)	0.407*	[0.209]
Years of schooling	6.319	(3.711)	5.519	(3.359)	-0.801***	[0.055]
Position/Status of the main job:						
Self-Owned Business (SOB)	0.244	(0.430)	0.234	(0.423)	-0.010	[0.007]
SOB with non-permanent worker	0.262	(0.440)	0.259	(0.438)	-0.003	[0.008]
SOB with permanent worker	0.033	(0.179)	0.022	(0.148)	-0.011***	[0.003]
Worker	0.347	(0.476)	0.373	(0.484)	0.026***	[0.008]
Non Paid Worker	0.010	(0.099)	0.010	(0.101)	0.000	[0.001]
Household Characteristics						
Max years of schooling	8.974	(3.719)	8.381	(3.398)	-0.593***	[0.056]
Dependency ratio	0.648	(0.643)	0.792	(0.692)	0.145***	[0.010]
Urban area	0.338	(0.473)	0.334	(0.472)	-0.004	[0.010]
Receive the KPS from Postman	0.160	(0.367)	0.227	(0.419)	0.067***	[0.021]
Number of households	19,032		7,180		26,212	

This table presents the averages of various outcome variables and household characteristics for treated and non-treated households and provides t-test of households who received the information but were no among Raskin beneficiaries. ***; **; * indicate the t-test significance differences at the 1% level; 5% level; and 10% levels respectively. The numbers inside brackets represent standard deviations.

Table A.6. Outcome Variable and household's characteristics Between Treatment and Control Groups of BLSM Beneficiaries

	Did Households receive information?				Difference	
	No		Yes			
	1	2	3	4	5	6
Monthly Raskin Bought (Kg)	6.007	(4.331)	5.993	(3.783)	-0.014	[0.203]
BLSM fund was levied (%)	0.199	(0.399)	0.160	(0.367)	-0.039***	[0.014]
PMT Score	13.290	(0.384)	13.302	(0.329)	0.012	[0.013]
Village Characteristics						
Ln Distance to Nearest District office	3.130	(1.207)	2.884	(1.214)	-0.246***	[0.047]
Ln Distance to Post office	2.213	(1.535)	1.781	(1.274)	-0.432***	[0.063]
Availability of Asphalt Road in the village	0.571	(0.495)	0.735	(0.442)	0.164***	[0.020]
Road can be accessed for a car	0.763	(0.425)	0.912	(0.284)	0.149***	[0.019]
Cultural Mono	0.706	(0.456)	0.786	(0.410)	0.080***	[0.018]
Availability Access to the National TV Station	0.502	(0.500)	0.527	(0.499)	0.025	[0.020]
Local Leader Directly Elected	0.884	(0.320)	0.809	(0.393)	-0.075***	[0.010]
Sea Transport	0.045	(0.208)	0.055	(0.229)	0.010	[0.009]
Padi as main Agriculture Product	0.395	(0.489)	0.453	(0.498)	0.058***	[0.018]
Slum Area	0.063	(0.243)	0.085	(0.278)	0.022**	[0.009]
Head of Village Characteristics						
Male	0.926	(0.262)	0.919	(0.272)	-0.007	[0.009]
Age	43.967	(9.836)	44.107	(9.642)	0.139	[0.360]
Education:						
No Education	0.050	(0.217)	0.013	(0.113)	-0.037***	[0.010]
Primary	0.078	(0.268)	0.014	(0.116)	-0.064***	[0.013]
Junior High	0.183	(0.387)	0.136	(0.342)	-0.048***	[0.016]
Senior High	0.465	(0.499)	0.523	(0.500)	0.057***	[0.019]
University	0.036	(0.188)	0.047	(0.211)	0.010	[0.006]
Head of Household Characteristics						
Widow	0.141	(0.348)	0.138	(0.345)	-0.004	[0.007]
Age	48.531	(14.121)	49.203	(13.465)	0.672**	[0.340]
Years of schooling	4.854	(3.725)	5.682	(3.392)	0.829***	[0.099]
Position/Status of the main job:						
Self-Owned Business (SOB)	0.213	(0.410)	0.241	(0.427)	0.027**	[0.011]
SOB with non-permanent worker	0.390	(0.488)	0.285	(0.452)	-0.105***	[0.016]
SOB with permanent worker	0.019	(0.137)	0.024	(0.153)	0.005	[0.003]
Worker	0.281	(0.449)	0.350	(0.477)	0.069***	[0.012]
Non Paid Worker	0.013	(0.115)	0.010	(0.100)	-0.003	[0.002]
Household Characteristics						
Max years of schooling	7.412	(4.055)	8.533	(3.357)	1.122***	[0.118]
Dependency ratio	0.742	(0.702)	0.818	(0.708)	0.075***	[0.015]
Urban area	0.224	(0.417)	0.305	(0.460)	0.080***	[0.014]
Receive the KPS from Postman	0.148	(0.355)	0.237	(0.425)	0.089***	[0.017]
Number of households	3,810		9,432		13,423	

This table presents the averages of various outcome variables and household characteristics for treated and non-treated households and provides t-test of households who received the information but were no among BLSM beneficiaries. ***; **; * indicate the t-test significance differences at the 1% level; 5% level; and 10% levels respectively. The numbers inside brackets represent standard deviations.

Figures

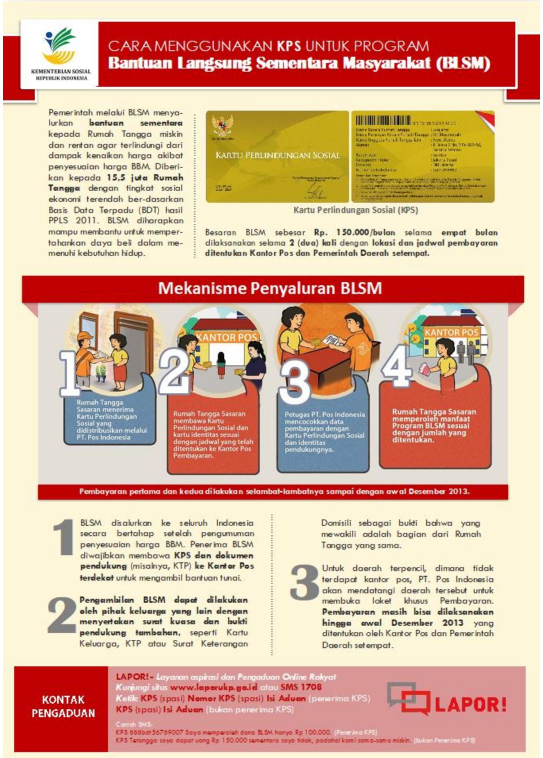
Figure B.1. The KPS Card

Front side of the KPS

Back side of the KPS

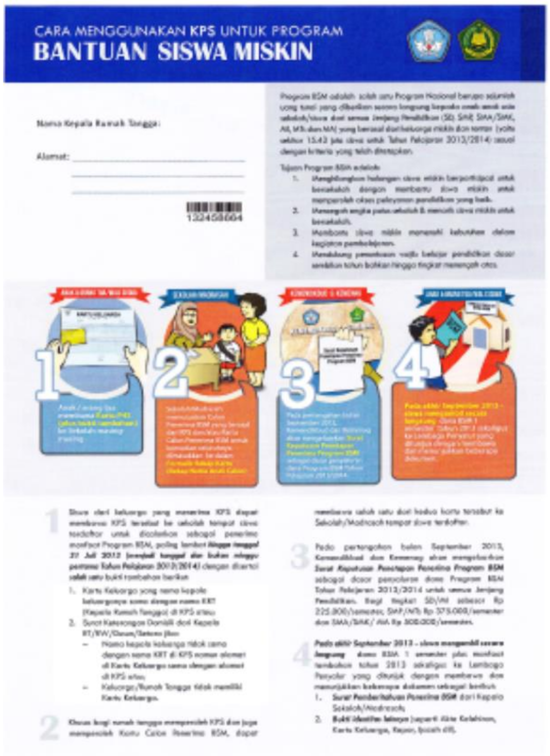
Figure B.2. Information included in the KPS package about:

Panel A: Complaint mechanism of the KPS Card



Panel B: How to access BLSM program

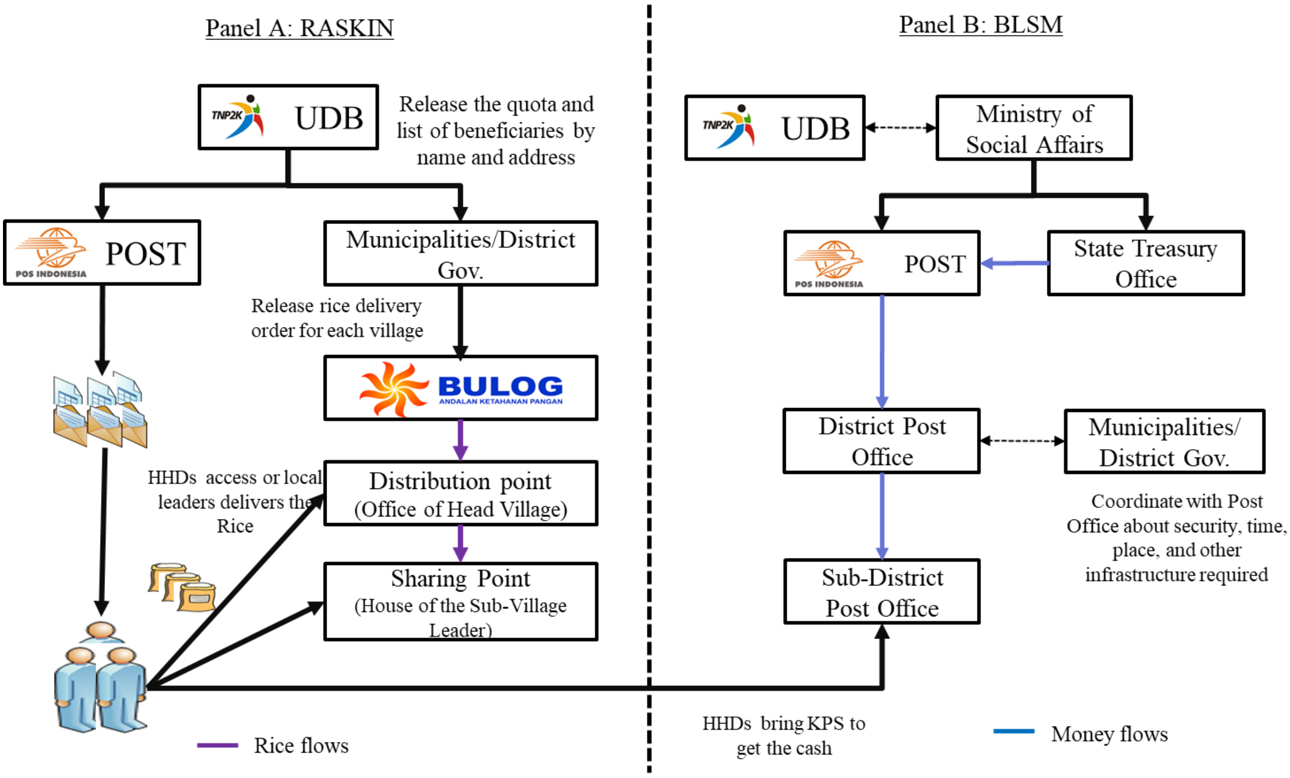
Panel C: How to access Raskin program



Panel D: How to access Scholarship program

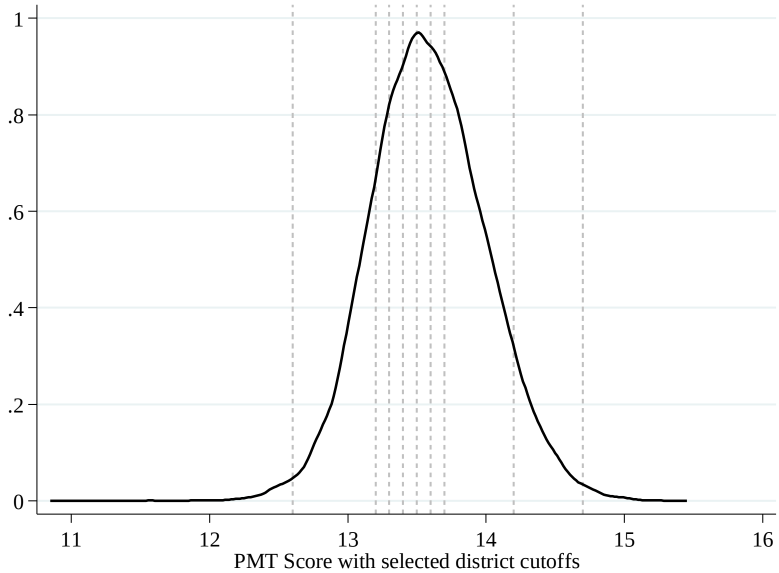
The figures present the information included in the KPS package. Panel A is about complaint mechanism of the KPS in case the household has problem about their eligibility. Panels B, C, and D show the mechanism as to how KPS holders can access the benefit from BLSM, Raskin, and Scholarship programs respectively.

Figure B.3. The Delivery Mechanism of Raskin and BLSM Programs



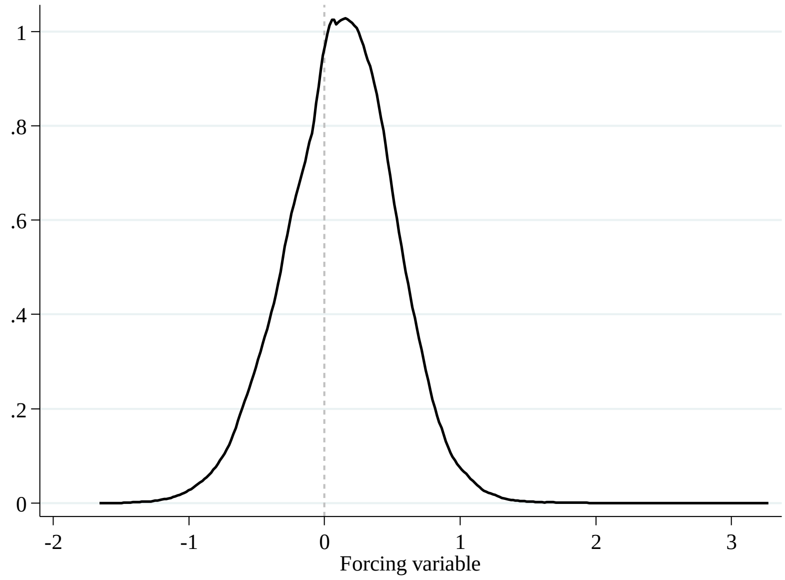
This figure shows the differences in delivery mechanism between the Raskin and BLSM programs. The distribution of the Raskin rice relies on the authority of village leaders, while the BLSM beneficiaries are extracted directly from the TNP2K's UDB database such that they should use their KPS to access the BLSM fund.

Figure B.4. The Distribution of Household's PMT Score and Selected District Cut-offs



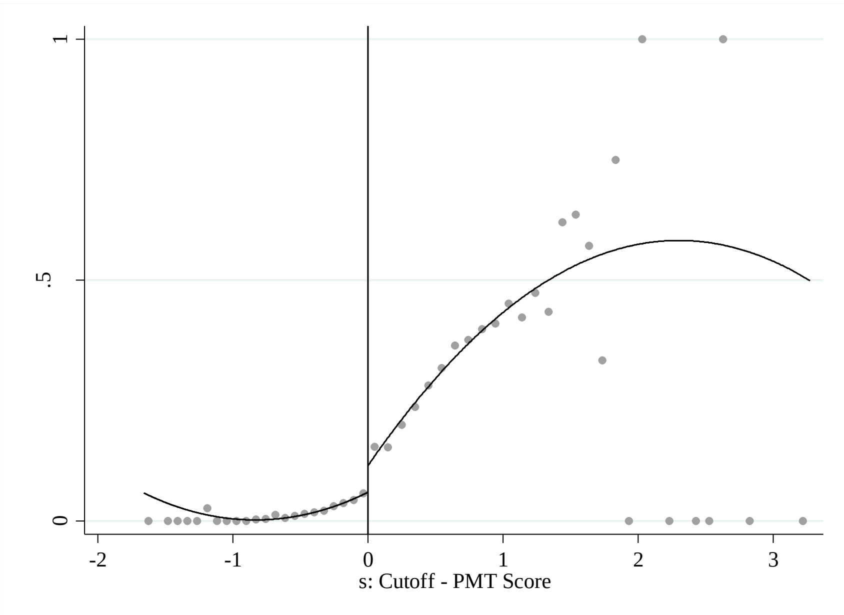
This figure presents the distribution of the household's PMT score, which is produced by applying the official PMT coefficients that are unique to all 482 districts of Indonesia in order to estimate each household's PMT score, thereby ensuring as close a comparison as possible with the official PMT used in developing the UDB, while the vertical lines represents the selected district's official cut-offs. The eligibility rule of the program is that households whose PMT score are below their district cut-offs would receive the information treatment.

Figure B.5. Distribution of Household's Running Variable with Cut-off = 0



This figure shows the distribution of the household's running variable, s_i, which is calculated by subtracting the district cut-off with the household's PMT Score. Due to this normalization and the eligibility rule of the program design, households would receive the information treatment if their running variables are positive or equal to zero, $s_i \geq \bar{s} = 0$ and they would not reveice the treatment if their running variables are negative or less than the threshold, , $s_i < \bar{s} = 0$.

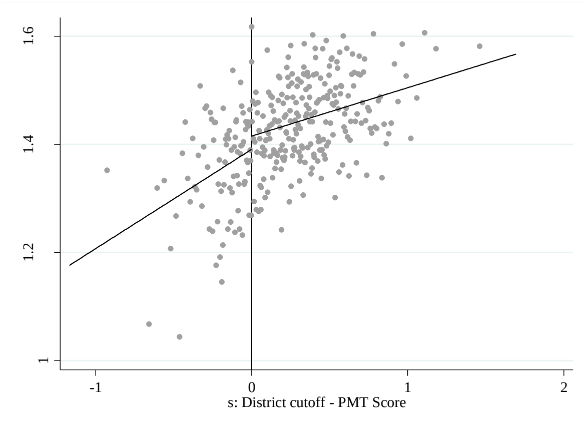
Figure B.6. The probability for receiving the information treatment given S



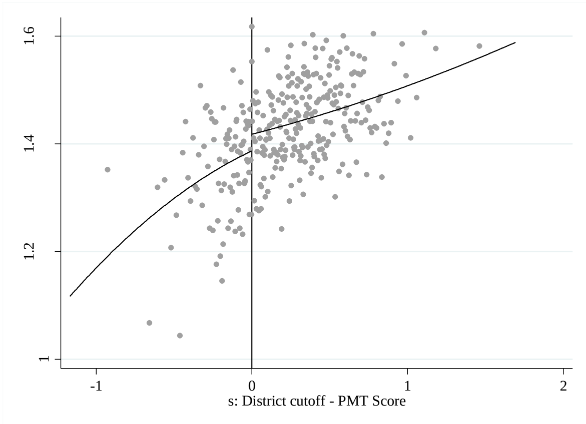
This figure shows the probability of receiving the information treatment given the running variable.

Figure B.7. Discontinuity of Outcome variable at Cut-off (s=0)

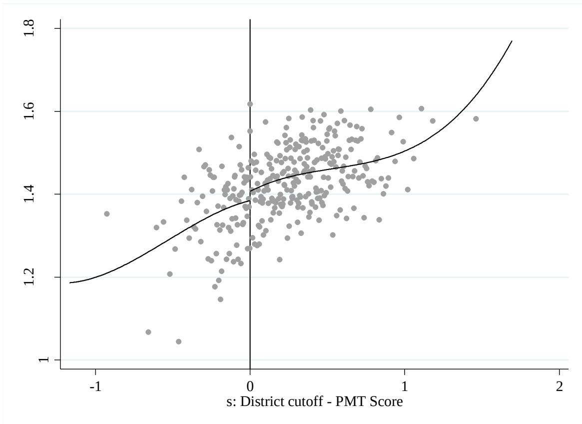
Panel A: Linear Order Polynomial



Panel B: Quadratic Order Polynomial



Panel C: Cubic Order Polynomial



These figures reoresent graphical illustration of our RD design of Log(Raskin Bought). The scatterplots are the average number within bins that are selected under IMSE-optimal quantile-spaced method using spacing estimators and the solid lines are the predicted outcomes, respectively, based on linear polynomial regression in Panel (A), quadratic polynomial regression in Panel (B), and Cubic polynomial regression in Panel (C).

Figure B.8. Report of Deduction of BLSM Fund

Translated as: Deduction of BLSM Fund at Village Cimanggu, Sub-District Cisalak, District Subang

Report:

Dear. Ministry of Home Affairs

KPS no………., I received BLSM and most of BLSM recipients in vil. Cimanggu, Sub-vil. Cisalak, Subang was levied by village local leader (Kades)

Please follow up this report.

This figure presents one of examples of household’s complaints about BLSM fund levied by village local leaders. This complaint was reported directly by the household to the President's Delivery Unit for Development Monitoring and Oversight Unit (*Unit Kerja Presiden Bidang Pengawasan dan Pengendalian Pembangunan* - UKP4)