FINDING THE POOR VS. MEASURING THEIR POVERTY: EXPLORING THE DRIVERS OF TARGETING EFFECTIVENESS IN INDONESIA

ADAMA BAH, SAMUEL BAZZI, SUDARNO SUMARTO, AND JULIA TOBIAS

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Finding the Poor vs. Measuring Their Poverty: Exploring the Drivers of Targeting Effectiveness in Indonesia

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ABSTRACT

Centralised targeting registries are increasingly used to allocate social assistance benefits in developing countries. This paper provides the first attempt to identify the relative importance of two key design issues for targeting accuracy: (1) which households to survey for inclusion in the targeting registry and (2) how to rank surveyed households. We evaluate the performance of Indonesia's Unified Database for Social Protection Programmes (UDB), the largest targeting registry in the world, which is used to provide social assistance to more than 25 million households. Linking administrative data with an independent household survey, we find that the UDB system is more progressive than previous targeting approaches used in Indonesia, leading to a decrease in benefit leakage to non-poor households. However, if poor households are not surveyed in the first place, even a perfect ranking method cannot prevent their exclusion. Under a simulation that considers enumerating and estimating proxy-means testing (PMT) scores for all households (as in a census), we estimate a one-third decrease in undercoverage compared to focusing on households that have been registered in the UDB. Investigating household- and community-level correlates of misenumeration and misclassification, we find evidence that local communities use different definitions of poverty and have better information on the welfare status of their members.

JEL classification: D61, I32, I38

Keywords: Targeting, Proxy-Means Testing, Social Protection, Poverty

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Abbreviations

BLT	*Bantuan Langsung Tunai* (Unconditional Cash Transfer)
Jamkesmas	*Jaminan Kesehatan Masyarakat* (Public Health Insurance)
Raskin	*Subsidi Beras Bagi Masyarakat Berpendapatan Rendah* (Rice for the Poor)
Rp	rupiah (Indonesian)
RT	*rukun tetangga* (neighbourhood association)
RW	*rukun warga* (community association)
Susenas	*Survei Sosial dan Ekonomi Nasional* (National Socioeconomic Survey)
Suseti	*Survei Sosial Ekonomi Rumah Tangga* (Household Socioeconomic Survey)
UDB	Unified Database for Social Protection Programmes (*Basis Data Terpadu untuk Program Perlindungan Sosial*)

1. Introduction

Social assistance programmes are currently estimated to cover as many as one billion people in the developing world (International Labour Organization 2010). These programmes are often targeted to the neediest population groups, which are identified based on socioeconomic status, in order to maximise their effectiveness in improving social welfare given a limited budget. However, identifying and reaching the intended beneficiaries can be challenging, especially in developing countries where a large part of the population works in the informal sector and official income registries do not exist. In the past 20 years, low- and middle-income countries have increasingly used centralised targeting registries to select recipients of social assistance programmes.[2] For such registries, basic household and individual information is typically collected for a subset of the population that is considered potentially eligible for social assistance (because conducting a full census of all households is usually cost prohibitive).[3] This information is then used to determine eligibility, most commonly based on proxy-means testing (PMT).[4]

This paper deals with two key challenges that arise in the development of any targeting registry. The first challenge is how to identify households for inclusion in the registry or, in other words, **who to survey** within the entire population. Properly addressing this issue is essential to ensuring that poor households are included in the registry in the first place, thereby avoiding what we refer to here as 'misenumeration' errors. The second challenge is **how to assess the eligibility of those surveyed**, that is, how to estimate their socioeconomic status in order to rank or classify them. The main concern in this step is to minimise what are referred to here as 'misclassification' errors that stem from the poor households surveyed being deemed ineligible and from non-poor (surveyed) households being wrongly classified as poor.

Misenumeration and misclassification have strong implications for targeting accuracy, which is commonly assessed using two key measures: leakage (or 'inclusion error'), when non-intended beneficiaries receive programme benefits, and undercoverage (or 'exclusion error'), when intended beneficiaries do not receive programme benefits (Cornia and Stewart 1995). Many programmes and countries today suffer from the adverse consequences of inaccurate targeting (Acosta et al. 2011). To date, however, little is known about the relative importance of household registration and ranking in determining the accuracy of targeting registries, as most existing studies focus on errors due to misclassification.[5]

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[2] Examples of countries using centralised targeting registries besides Indonesia include Brazil, Chile, Colombia, India, Mexico, and Philippines (see, for example, Castañeda et al. (2005) for a review of the experience of Latin American countries; Dreze and Khera (2010) for the Indian Below-Poverty Line Census).

[3] Compared with common population census questionnaires, targeting registry questionnaires collect more detailed socioeconomic information at household and individual levels. They are therefore generally administered to a subset of the population, rather than the full population, in order to limit costs.

[4] PMT scores are constructed based on simple socioeconomic indicators that are relatively easy to collect and less prone to misreporting than expenditures or income. These indicators are combined into a single measure of welfare using weights typically derived from consumption regressions estimated from an auxiliary survey. Using these predicted measures of welfare can be a cost-effective way to identify beneficiaries of social programmes to the extent that they are sufficiently accurate.

[5] This includes evaluations of targeting effectiveness (e.g., Skoufias et al. 2001; Banerjee et al. 2007), as well as most of the optimal targeting literature, which can be divided between studies comparing different targeting methods and studies focusing on the design of PMT formulas for ranking. Studies comparing the relative advantages of different targeting methods (e.g., Coady et al. 2004, Banerjee et al. 2007, Alatas et al. 2012 and 2013a, and Karlan and Thuysbaert 2013) find that no method clearly dominates in terms of commonly used objective performance measures. However, in general, the evidence suggests that community targeting is best for identifying the very poorest households. Other studies focusing on the design of optimal PMT formulas (e.g., Sumarto et al. 2007, Muller and Bibi 2010, and Bah 2013) show that targeting errors are unavoidable when using simple indicators, although the degree of error can be minimised with more careful selection of the proxies for

This paper provides the first attempt to assess the relative contribution of the household registration and ranking processes to the overall accuracy of a centralised targeting registry. We do so using Indonesia's newly developed household targeting registry and aim to identify priority actions for improving targeting effectiveness. Established in 2012, the Unified Database (UDB) for Social Protection Programmes is intended to cover the poorest 40% of the Indonesian population.[6] More than 25 million households have been registered in the UDB using an innovative approach based on a pre-listing of households to be surveyed, constructed through census-based poverty mapping (Elbers et al. 2003) and complemented with suggestions from local communities. These households were subsequently ranked by their predicted welfare, estimated using district-specific[7] PMT formulas. The UDB has been used to deliver more than US$4 billion annually (Rp 43 trillion) in central government social assistance (based on 2013 figures).[8] This includes the largest social assistance programmes in the country: a rice subsidy programme known as Rice for the Poor (*Subsidi Beras Bagi Masyarakat Berpendapatan Rendah* or Raskin), a health insurance programme known as Public Health Insurance (*Jaminan Kesehatan Masyarakat* or Jamkesmas), and an Unconditional Cash Transfer programme (*Bantuan Langsung Tunai* or BLT). Before UDB's establishment, beneficiaries of these programmes were selected using ad hoc targeting approaches.

Our analysis for this paper proceeds in three steps. First, we evaluate the targeting performance of the UDB against the performance of past approaches to beneficiary selection used for the three main social assistance programmes. We use data from an independent survey known as the Indonesian Household Socioeconomic Survey (*Survei Sosial Ekonomi Rumah Tangga* or Suseti), which were matched with UDB administrative data. Suseti contains information on household expenditures per capita, which is not in the UDB, as well as information on the receipt of Raskin, Jamkesmas, and BLT at baseline (i.e., before the establishment of the UDB).

We find that targeting using the UDB is more progressive than previous approaches to beneficiary selection. In particular, the UDB leads to a substantial reduction in leakage of benefits to non-poor households. This decrease in leakage is largest for Raskin, for which the proportion of the richest 60% of households receiving benefits is expected to fall from nearly 75% to 25%. Our findings highlight the trade-offs between undercoverage and leakage found in many studies of targeting effectiveness (Grosh and Baker 1995). There are, indeed, more limited improvements in terms of undercoverage, which can be due to both misenumeration and misclassification errors.

Second, we differentiate the contribution of the enumeration and the PMT-based ranking processes to targeting errors, and in particular undercoverage. Through an assessment of the counterfactual performance that would be observed if all households had been enumerated (as in a census), we find evidence of enumeration gaps in the UDB that lead to undercoverage of poor households. Under this hypothetical scenario, severe undercoverage of all programmes falls by about one-third relative to a

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consumption. One notable exception is Alatas et al. (2013b), which shows that self-targeting has the potential to reduce misenumeration errors at the registration stage.

[6] References to 'poor' and 'non-poor' in relation to the UDB are meant to distinguish on the one hand households in the bottom 40% which is the target coverage of the UDB, and on the other hand those in the upper 60% of the consumption distribution that are meant to be excluded from the UDB.

[7] Indonesia's administrative divisions proceed from province to district to subdistrict to village to hamlet. There were 497 districts at the time of the establishment of the UDB.

[8] In June 2013, the Government of Indonesia announced a reduction in fuel subsidies, accompanied by a set of four compensation programmes to mitigate the reduction's effect on poor and vulnerable households.

targeting system based only on those households actually included in the UDB. Depending on the social planner's welfare function (i.e., the relative weights on the poorest households in the population), our findings suggest large gains from reallocating scarce administrative resources towards increasing survey coverage to minimise undercoverage of poor households in the UDB. In particular, we show that increased enumeration costs to cover the full population would amount to about 11% of the value of additional benefits that would be received annually by households from the poorest 30%. In other words, there should be a stronger focus on ensuring that an adequate number of households are surveyed. If poor households are not enumerated in the first place, even a perfect PMT algorithm cannot prevent their exclusion.

Third, we identify household- and community-level correlates of misenumeration and misclassification. Ownership of household assets that are difficult to observe and are not recorded in the UDB is associated with a lower probability of registration in the UDB. However, for households that are nevertheless registered, ownership of such assets is associated with a greater potential of being misclassified as poor. Our findings also suggest some form of strategic interaction with other social programmes during the UDB registration process. For example, receipt by households of informal support from (religious) nongovernmental organisations is associated with a higher likelihood of registration in the UDB. Furthermore, we find mixed evidence on the role of local (neighbourhood) officials in the targeting process. Households residing in villages with elected neighbourhood heads are more prone to exclusion errors. This may be due to 'voter capture' in which preferential treatment in the targeting process may be given to those residents who participate in neighbourhood activities including local elections (Kurasawa 2009).

Our paper contributes to the literature in public and development economics on optimal targeting of social programmes. Most studies use a single survey to identify intended and actual recipients, that is, who is poor and who is receiving government benefits. However, relying solely on household self-reporting on whether they receive benefits does not allow for a full understanding of what happens at the multiple stages of the targeting process before benefits are delivered to households. To our knowledge, this paper provides the first analysis based on actual administrative data on household eligibility for government social programmes linked with data on household expenditures from an independent survey. Using administrative data allows us to identify the relative contribution to overall targeting accuracy of (1) the decision on which potentially poor households to survey and (2) the estimation of their socioeconomic status based on the data collected. As a result, we are able to prioritise policy options to minimise the potential exclusion of the poorest households from increasingly used targeting registries of the sort we study in Indonesia.

Our findings have important implications for ongoing policy debates in developing countries concerning the design of efficient and equitable targeting registries. Overall, our results provide further evidence on the difficulty of accurate targeting in countries like Indonesia that have considerable clustering of households around the poverty line. Nevertheless, the research design allows us to clarify how improvements in the enumeration process can lead to large gains in overall targeting effectiveness.

The remainder of the paper is organised as follows. Section 2 provides background information on Indonesia's UDB. Section 3 presents the Suseti survey and its features. Section 4 assesses the predicted targeting accuracy of the UDB. Section 5 explores the determinants of UDB accuracy. Section 6 concludes with policy recommendations.

2. The Unified Database for Social Protection Programmes

In this section, we describe the two main steps in establishing a centralised targeting registry of 25 million households ranked according to their socioeconomic status: data collection (enumeration) and PMT modelling (ranking).[9] First, the data collection stage involved pre-identifying all potentially eligible households that should be surveyed. Given the lack of accurate pre-existing data on which households are the poorest, the government adopted a new approach combining administrative data from the 2010 Population Census and input from local communities.[10] Second, the PMT modelling stage entailed incorporating proxies for consumption-based welfare measures and accounting for the socioeconomic diversity across regions.

2.1 Data Collection

The establishment of the UDB was motivated by evidence that inaccurate targeting of Indonesia's main social protection programmes was a major obstacle to the effectiveness of the national poverty reduction strategy. Previous studies revealed that these programmes suffered from significant undercoverage of poor households and leakage to non-poor households (e.g., World Bank 2012). The targeting errors were believed to be due largely to coverage and quality gaps in the previous censuses of the poor used to identify beneficiaries of the BLT programmes implemented in 2005 and 2008.[11] Households surveyed in these data collection efforts were identified based mainly on subjective consultation of enumerators from Statistics Indonesia (*Badan Pusat Statistik* or BPS) with village leaders (see, for example, SMERU 2006).

The UDB was intended to cover a greater number of households and to avoid relying exclusively on subjective nominations from community leaders. The registration of households in the UDB followed a two-step approach: first, a 'pre-listing' of households to be surveyed produced through a poverty mapping exercise and, second, incorporation of suggestions from the community in the field to amend and complete the survey pre-listing.

The first step was intended to mitigate the undercoverage that had plagued previous data collection efforts in 2005 and 2008 and to ensure that a sufficient number of households were surveyed. A poverty mapping exercise was conducted using the Elbers et al. (2003) methodology and the 2010 Population Census to estimate household welfare (approximated by per capita consumption) for the entire population. Target enumeration quotas were estimated using district-specific consumption-based poverty lines from the 2010 National Social and Economic Survey (*Survei Sosial dan Ekonomi Nasional* or Susenas) to account for income differences across Indonesia's 497 districts.[12] All households in each village with a predicted per capita consumption level below the enumeration quota cut-off were included on a pre-listing (by name and address) to be surveyed for inclusion in the UDB.

[9] Detailed information on the full process followed in establishing the UDB is available in TNP2K (2014).

[10] Alternative approaches include surveying households that request it or conducting a census in the poorest areas (e.g., Skoufias et al. 2001; Camacho and Conover 2011; and Karlan and Thuysbaert 2013).

[11] These two cash transfer programmes were designed to provide temporary compensation to protect poor households against the shocks associated with fuel subsidy reductions. See Bazzi et al. (2014) for an evaluation of the 2005 programme's impact on household consumption. In 2013 the BLT programme was renamed Short-Term Unconditional Cash Transfers (*Bantuan Langsung Sementara Masyarakat* or BLSM). For simplicity and because the programme is still often referred to by its original name, this paper uses 'BLT' to refer to both the previous and newer variants of this programme.

[12] Administered to a sample of households representative at the district level, Susenas includes a detailed consumption module that is used to estimate poverty lines.

In the second step, suggestions from communities were incorporated during the enumeration in the field by BPS staff responsible for registration of households on the pre-listings. In nearly all districts, enumerators and/or community leaders removed from the survey pre-listings those households that were considered non-poor or could not be found (e.g., due to relocation or death). The guidelines for enumerators also stipulated that households that were not on the pre-listings could be registered if the household (1) 'appeared poor' to the enumerators or (2) was designated as poor by other poor households in the community.

The initial budget allowed for coverage of 50% of the Indonesian population. In practice, only 43% of all households were surveyed nationally, with varying coverage across districts. This was lower than expected and can be traced to the second step in the data collection process. Some households on the pre-listing were not actually surveyed in the field (e.g., because they were considered non-poor), which may have resulted in exclusion of some households. In addition, a limited number of households were added to the pre-listings due to reluctance among enumerators and community leaders for several reasons (SMERU 2012).[13]

2.2 PMT Modelling

The UDB registration survey collected household-level information such as demographics, housing characteristics, sanitation, access to basic domestic energy services, and asset ownership, along with information on individual household members including age, gender, schooling, and occupation. Using this information, households were ranked by their predicted welfare following a PMT approach. PMT formulas were constructed based on district-specific consumption regressions to account explicitly for heterogeneity across regions.

Although the PMT approach can be a cost-effective means of identifying beneficiaries of social programmes in the absence of an up-to-date household registry with reliable income data, it is also prone to errors (e.g., Grosh and Baker 1995). In particular, targeting errors may occur due to weak predictive performance of the consumption models within the estimation sample (e.g., due to constraints on the set of socioeconomic variables available for use in the PMT regressions). Furthermore, overfitting, which is more likely to occur when a large number of predictors are included in the models and/or when the estimation is based on a small sample, may limit the validity and precision of the PMT formulas outside the estimation sample.

In the remainder of the paper, we investigate the overall accuracy of Indonesia's targeting database of 25 million households established through the data collection and PMT classification stages described above.

[13] In some communities, local leaders were reluctant to survey a high number of households, particularly households not considered to be poor. Their main concerns related to building household expectations about receiving programme benefits by surveying many households, when such expectations might later be disappointed (SMERU 2012). In addition, there was limited understanding that being surveyed would not automatically result in being selected for programmes, and local leaders may have feared that surveying non-poor households would increase the likelihood that these households would be selected to receive benefits for which they are not eligible. Similar issues had created social unrest in several communities in the past, especially during implementation of the 2005 census of the poor for the first BLT programme (SMERU 2006). It should also be noted that surveyors were paid a fixed monthly salary, rather than being paid per household surveyed, which may have reduced incentives to achieve greater coverage of households.

3. The Indonesian Household Socioeconomic Survey

To assess the accuracy of the UDB, we use data from the Indonesian Household Socioeconomic Survey or Suseti, which was collected by an independent survey firm and contains detailed information on household living conditions.

3.1 The Suseti and its Link with the UDB

The Suseti sample comprises 5,682 households[14] located in 600 villages spread across 6 districts in the provinces of Central Java (Pemalang and Wonogiri districts), Lampung (Bandar Lampung and Central Lampung districts), and South Sumatra (Ogan Komering Ilir and Palembang districts). The provinces were selected to represent a wide range of Indonesia's diverse cultural and economic geography, and the six districts were selected within areas where the Indonesian Conditional Cash Transfer Programme for Families (*Program Keluarga Harapan* or PKH) was to expand in 2011.[15] In one randomly selected hamlet/neighbourhood (*rukun tetangga* or RT/ *rukun warga* or RW) within each of the 600 villages, the Suseti questionnaire was administered to nine households randomly selected from among those that met the PKH demographic eligibility criteria of having an expectant mother or at least one child under the age of 16 years old.[16] A longer version of the same questionnaire was also used to collect data from each neighbourhood head.

Suseti comprises a baseline collected in March 2011, as well as an end line following the same households and collected in February 2012. Given the purposes of this study, we use the baseline data because it includes a more comprehensive set of socioeconomic variables and because the survey was administered closer to the July–August 2011 timing of the data collection for the UDB.[17]

Although the Suseti sample is not statistically representative of the whole country (or even the given districts), it has several unique features that make our results internally valid in terms of our primary goal of evaluating and decomposing the targeting performance of the UDB. First, the survey incorporated a rigorous matching process to enable identification of households registered in the UDB. We conducted desk-based matching using the names and addresses of household heads and spouses and also verified the matching results in the field.[18] The field-based verification process makes 'false positive' matches very unlikely, however, a small number of 'false negative' matches may occur (i.e., Suseti households

[14] The survey initially included 5,998 households, but there was attrition of about 5% (or 316) original households between the baseline and end line waves. We focus in the paper on the 5,682 households surveyed in both waves. Attritors do not systematically differ from non-attritors along baseline characteristics used in Suseti and in the UDB to construct the PMT. Results available upon request.

[15] For more detailed information on the design and sampling of the survey, which was originally collected to compare different targeting methods in a high-stakes experiment, see Alatas et al. (2013a and b).

[16] According to nationally representative household survey data from 2010 (Susenas), within the entire Indonesian population, about two-thirds of households have at least one child aged below 16 years old.

[17] An additional reason for using the baseline data is that the survey was administered before the government conducted any socialisation or targeting for PKH, while the end line was administered after the PKH programme started. Thus, we avoid using the consumption data in the end line, as it may potentially reflect nonrandom shocks associated with the PKH programme.

[18] Before the Suseti end-line survey was conducted, a listing of all households to be surveyed was constructed based on baseline respondents. This list was electronically matched with the UDB using household characteristics such as the addresses and names of the household head and spouse. This list was also matched with the enumeration pre-listing in order to identify households that were initially on this list but were not registered in the UDB. During the end-line survey fielding, enumerators and community leaders were asked to verify that the electronic matches were correctly identified. They were also asked to identify manually any other matches not yet identified by comparing the Suseti listing with the UDB registry.

who were also in the UDB but the match was not detected) due to the difficulty in recognising different versions of names. The expected effects of such potential undermatching would be to inflate slightly the estimated errors of exclusion and to deflate slightly estimated errors of inclusion.

Our evaluation of the UDB's targeting performance is therefore based on comparing actual administrative data on household eligibility status for government social programmes (from the UDB) and data on their expenditures (from Suseti). This feature allows a better understanding of what happens at the multiple stages of the targeting process before benefits are delivered to households, including the decision on which potentially poor households should be surveyed, as well as the process of estimating their socioeconomic status based on the data collected.[19]

A second important feature of Suseti is the availability of information on receipt of Indonesia's main social protection programmes (Raskin, Jamkesmas, and BLT) before establishment of the UDB. These programmes relied in the past on different methods of identifying beneficiaries, such as using previous censuses of the poor (BLT) and/or nominations from community leaders. This allows us to compare the performance of the centralized UDB targeting registry, with more ad hoc (baseline) targeting approaches. We are therefore able to evaluate the change in targeting accuracy for programmes transitioning to using the UDB.[20]

Suseti also includes all the indicators used to calculate households' PMT scores in the UDB. This allows simulating the PMT process used in Indonesia under the hypothetical scenario of all households having been surveyed for inclusion in the UDB, rather than only the subset of households expected to be poor. We are thus able to distinguish between targeting errors that are due to 'enumeration errors', that is, poor households not registered in the UDB and those associated with the PMT estimation process.

Furthermore, Suseti contains other types of information relevant to identifying determinants of targeting errors, such as household participation in the community, difficult-to-observe assets, and exposure to shocks. The survey component administered to the head of each hamlet/neighbourhood also collects information on community-level characteristics such as its geographic remoteness, the mode of selection of its head, and his/her social networks with other community members.[21]

Table 1 shows the results of the matching process used to determine which households from the Suseti survey are registered in the UDB. Overall, 41% of the PKH eligible population in the Suseti districts is registered in the UDB. In Suseti, of the 5,682 households surveyed, 2,444 or 43% are registered in the UDB.[22] Given regional variation in rates of poverty and vulnerability, this percentage differs

[19] The targeting accuracy of social programmes is measured based on a comparison of the discrepancy between intended and actual recipients, that is, who is poor (often based on household expenditures) and who is receiving government benefits. Existing evaluations of targeting accuracy (e.g., Coady et al. 2004) are usually done using data on both of these key indicators from a single survey. As a result, these evaluations rely on households to self-report whether they receive benefits rather than using administrative data directly.

[20] At the time of the fielding of Suseti (and matching with the UDB) in early 2012, the UDB had not yet been used for targeting purposes. However, it was known which households were to be included in the beneficiary lists from the UDB provided to these programmes, based on their PMT score rankings.

[21] RTs are neighbourhood associations with all households registered as living in the area as members. By law, RTs are meant 'to help smooth the execution of duty in administration, development, and social activities at the village and town level' (Kurasawa 2009).

[22] Suseti was also matched with the enumeration pre-listings; an additional 1,048 households that were removed from these pre-listings and are therefore not registered in the UDB were identified.

across districts, from 28% of the Suseti sample in Wonogiri to 52% in Central Lampung and Pemalang. Overall, however, the high correlation in the shares of the population registered in the UDB in the Suseti sample and in the total population increases confidence in the accuracy of the matching exercise, which is important to ensuring valid estimates of targeting errors in the UDB.[23]

Table 1. Results of Dataset Matching: Share of UDB Households in the Total Population and in Suseti

	Total Population			Suseti Sample		
District	UDB	All	Share in UDB (%)	UDB	All	Share in UDB (%)
Bandar Lampung	81,003	223,730	36	215	459	47
Central Lampung	58,576	132,554	44	739	1408	52
Ogan Komering Ilir	82,110	226,705	36	344	1056	33
Palembang	53,693	149,010	36	380	826	46
Pemalang	121,031	211,100	57	490	949	52
Wonogiri	50,040	138,369	36	276	984	28
All	446,453	1,081,468	41	2,444	5,682	43

Notes: This table shows the percentage of PKH-eligible households, that is, households with children aged under 16 years old, registered in the UDB, comparing UDB/Susenas data with Suseti data for the six sample districts. The first group of columns shows the total number of households with children aged under 16 years old recorded in the UDB ('UDB' column) and in the full population from Susenas 2010 data ('All' column). The second group of columns shows the number of households from the Suseti data successfully matched with the UDB administrative data ('UDB') and the total number of households in Suseti ('All').

3.2 *Comparison of UDB-Registered and Non-registered Households*

Table 2 provides an initial glimpse into the UDB's performance in reaching the poorest households, through a comparison of the socioeconomic characteristics of Suseti households registered in the UDB and those not included ('non-UDB'). Households registered in the UDB appear significantly poorer, with monthly per capita expenditure levels 1.4 times lower on average than those of non-UDB households. Compared with non-UDB households, UDB households tend to have significantly more family members and children. UDB household heads also have about two fewer years of schooling, and fewer among them are male and working, compared with non-UDB household heads.

Table 2 also shows that UDB households are more likely than non-UDB households to have previously received benefits from one or more of the national social protection programmes distributed before implementation of the UDB.[24] For the BLT cash transfer programme distributed in 2008, 58% of UDB households reported having been recipients compared with 26% of non-UDB households; the figures

[23] Matching rates in the urban districts of Bandar Lampung and Palembang appear relatively higher than the share of the population registered in the UDB, suggesting that local-level characteristics may affect the matching rate. However, similar results to table 1 are obtained when considering district-specific average village shares of UDB households in the population and in the Suseti sample.

[24] Note that because the Suseti data were collected before any of these social programmes had begun to use the UDB for selecting beneficiaries, these baseline figures indicate numbers of previous beneficiaries entering into the UDB and do not show the UDB's anticipated effects on programme targeting outcomes, which are explored later.

are similar for the Jamkesmas health fee waiver programme (59% and 33%, respectively). For the Raskin subsidised rice programme, 92% of UDB households reported having received programme benefits compared with 71% of non-UDB households.[25]

Table 2. Socioeconomic Characteristics of Households in the Suseti

	All Households	UDB	non UDB	t-stat
Demographic Characteristics				
Household size	4.8	4.9	4.6	–6.03***
Number of Children aged 0–15 years	1.7	1.8	1.6	–7.36***
Household head aged	44.4	44.1	44.5	1.28
Male household head	0.95	0.93	0.95	2.50**
Household head schooling years	6.9	5.9	7.7	16.84***
Household head works	0.93	0.92	0.94	2.15**
Household head works in agricultural sector	0.45	0.46	0.44	–1.79*
(Baseline) household expenditures per capita, IDR	575,766	471,443	654,499	16.54***
Receipt of Social Assistance Programmes				
Raskin subsidised rice	0.80	0.92	0.71	–19.59***
Jamkesmas health waiver programme	0.44	0.59	0.33	–20.19***
BLT unconditional cash transfer in 2008	0.40	0.58	0.26	–25.44***

Notes: This table reports averages for all households in Suseti followed by a breakdown for households in the UDB and not in the UDB. Cells with values less than one are variables reporting a proportion. Per capita expenditures are nominal rupiah values as reported in the baseline survey. The t-stat is based on a two-sided test for difference in means between UDB and non-UDB households. Stars indicate significance at the 1% ***, 5% **, and 10% * level.

The finding that UDB households are poorer than non-UDB households is further supported in figures 1a and 1b, which indicate the targeting performance of UDB. Figure 1a confirms the findings of table 2 in showing that UDB households are on average poorer than non-UDB households are. However, there appears to be a rather large overlap in the consumption distributions, suggesting that a sizable share of poor households is not in the UDB.[26] Figure 1b plots the probability of being in the UDB against per capita consumption and shows a clear inverse relationship. Households with the lowest consumption levels have a probability of being in the UDB of more than 60%, whereas this probability is lower than 20% for households with the highest consumption levels. In theory, these probabilities would ideally be 100% and 0%, respectively. However 'perfect targeting' performance is impossible in practice. The next section explores how the expected UDB targeting outcomes fare regarding baseline benchmarks for the three major social assistance programmes.

[25] It is notable that the average numbers of households reporting receiving benefits from each programme appear to be quite high, given that each of these programmes is intended to cover about 20% to 30% of households on average nationally. This could reflect either specificities of the Suseti sample or the dilution of programme benefits. For Raskin, for instance, there is evidence that the fixed allocations of 15 kilograms of subsidised rice normally targeted to poor households are often distributed more widely, including among the entire community (SMERU 2008). World Bank (2012) also finds using the nationally representative Susenas, that 50%, 30%, and 27% of households report receiving respectively Raskin, Jamkesmas, and BLT.

[26] Note that there may be measurement error affecting the spread of the consumption distribution.

Figure 1A. Distribution of per Capita Expenditures: UDB and Non-UDB Households in the Suseti Sample

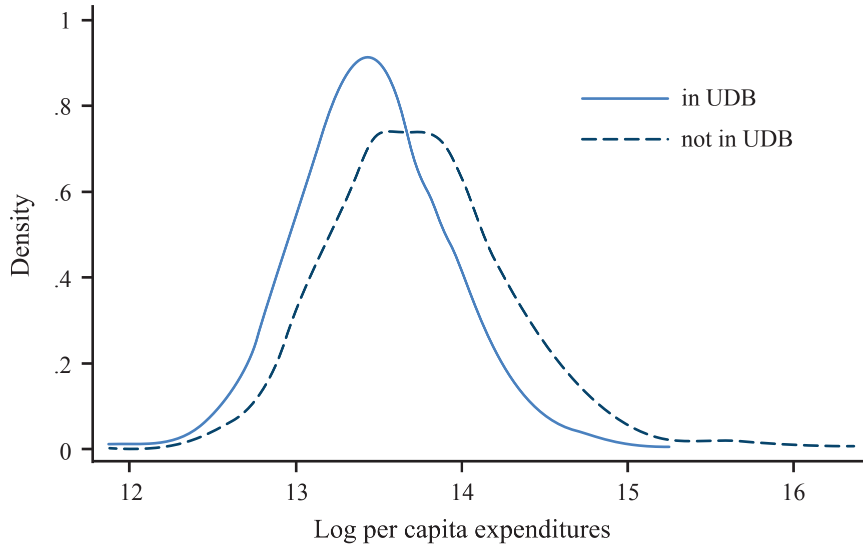
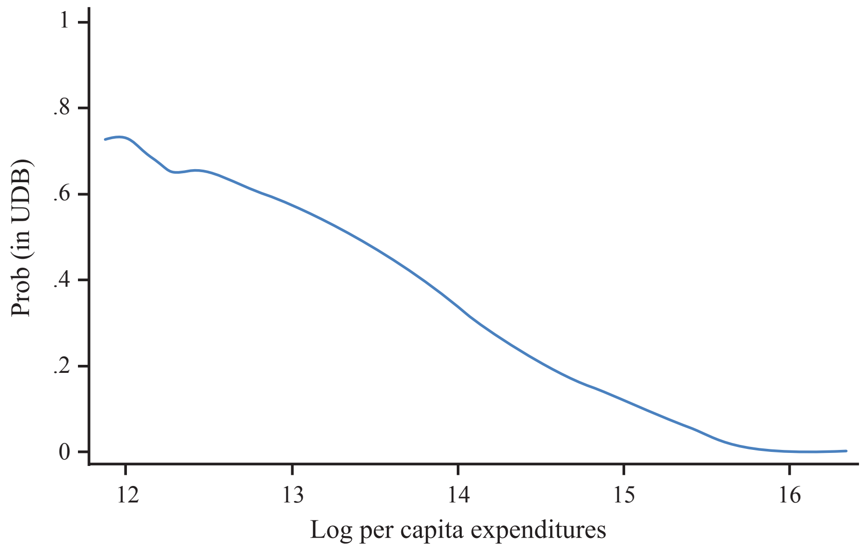


Figure 1B. Probability of being in the UDB and Actual per Capita Expenditures



Notes: Figure 1(a) plots the kernel density of log household expenditures per capita separately for Suseti households registered and not registered in the UDB. Figure 1(b) plots the local linear probability of being in the UDB against log expenditures.

4. Evaluating the Targeting Performance of the UDB

This section analyses in greater depth the targeting performance of the UDB, taking advantage of the matched Suseti-UDB data. Section 4.1 explains the methodology used to assess baseline and expected targeting accuracy of social programmes in Indonesia. Section 4.2 presents the UDB's targeting performance. Section 4.3 takes the analysis further by disentangling errors resulting from the enumeration process and PMT classification errors.

4.1 Methodology for Assessing the Targeting Accuracy of the UDB

A large literature examines different measures and methodologies for estimating targeting accuracy (see Coady et al. 2004 for a review). Commonly used measures of targeting outcomes include undercoverage and leakage (Cornia and Stewart 1995), the distributional characteristic (Coady and Skoufias 2004), and the Coady-Grosh-Hoddinott measure (Coady et al. 2004). In this paper and in line with most of the literature, we use undercoverage and leakage as our main measures of targeting outcomes. Undercoverage—or exclusion error—is defined as the share of households below a given poverty threshold that are not receiving programme benefits. We consider two thresholds specifically and define **undercoverage** using the 30th percentile of household actual (adjusted) per capita consumption in the Suseti sample, and **severe undercoverage** using the 10th percentile.[27] Conversely, leakage, or inclusion error, is defined as the share of households that are above a given threshold and yet receive benefits. Similar to undercoverage, we use two thresholds and define leakage using the 60th percentile and **severe leakage** using the 80th percentile of the adjusted per capita consumption distribution. Key results are robust to alternative thresholds.

As described earlier, we assess the targeting performance of the UDB against the baseline targeting performance of the main social assistance programmes (Raskin, Jamkesmas, and BLT). More specifically, we consider the performance expected from the use of lists of eligible beneficiaries from the UDB. Focusing on pre-determined eligibility based on the UDB, rather than on reported receipt of benefits, allows us to emphasize the potential for the newly established UDB to improve targeting outcomes, setting aside other programme implementation issues that might affect benefit delivery. However, some discrepancy between the expected and actual UDB targeting errors might occur depending on the degree of compliance with the beneficiary lists extracted from the UDB in the field. For Jamkesmas and BLT, the amount of discrepancy is expected to be relatively small because eligibility cards were printed directly based on the UDB. For Raskin, more discrepancy is anticipated between expected and actual targeting outcomes due to the longstanding community practice of sharing rice benefits across nominally eligible and ineligible households.[28]

Baseline targeting errors are calculated by comparing reported programme receipt to household per capita consumption. Expected UDB targeting errors are calculated for households registered in the UDB by comparing actual per capita consumption (from Suseti) with the PMT scores (from the UDB)

[27] These levels correspond closely to the thresholds used by the Indonesian government to determine eligibility for its main social assistance programmes; BLT, Jamkesmas, and Raskin all cover roughly the poorest 30% of households in the country, while the eligibility threshold for PKH is close to the poorest 10%.

[28] One of the objectives of establishing the UDB is to reduce benefit dilution, which decreases significantly the share of benefits received by the target population. Raskin beneficiaries, for instance, purchased on average 3.8 kilograms of rice monthly, instead of the intended 15 kilograms, 'due to community-level sharing of benefits by non-target households' (World Bank 2012).

used to produce beneficiary lists based on each programme's eligibility threshold. Any household in the Suseti sample not found in the UDB through the matching process is considered a non-recipient.

The comparison of baseline and expected UDB targeting errors (undercoverage and leakage) reveals the change in targeting performance due to the transition of the programmes to using the UDB for beneficiary selection. Switching to the UDB implies changes not only in which households will receive programme benefits but also in the total number of beneficiaries (i.e., programme coverage). These differences in coverage make it difficult to compare across time and across programmes. Therefore, we first present standard undercoverage and leakage measures to assess the overall change in targeting performance before (baseline) and after the UDB. We then isolate the change expected solely from beneficiary identification using the UDB lists by computing UDB undercoverage and leakage at an unchanged (baseline) coverage level.

We also address a notable limitation of standard undercoverage and leakage measures (see, for example, Coady and Skoufias 2004 and Coady et al. 2004), which weight all households equally, regardless of their position in the consumption distribution. For instance, when measuring undercoverage for a programme intended to cover the poorest three deciles of the consumption distribution, no distinction is made between the exclusion of a household in the poorest 5% and that of a household in the 29th percentile, even though from a welfare perspective, excluding the former represents a more serious error. We therefore also present the expected incidence of benefits across all consumption deciles to provide a more detailed assessment of the distributional performance of the UDB.

4.2 Results: UDB Targeting Performance

In this section, we evaluate the overall targeting performance of the UDB through the changes in targeting accuracy that can be expected from the transition of the three main Indonesian social assistance programmes to using the UDB. Column 1 of table 3 shows that, at baseline, 80%, 44%, and 39% of all Suseti households report to have previously received, respectively, Raskin, Jamkesmas, and BLT. Compared with Jamkesmas and BLT, Raskin's substantially higher coverage levels have led to (1) very low baseline undercoverage: less than 11% of the poorest three deciles have not received the subsidised rice benefits and (2) high leakage: 74% of the richest four deciles have received benefits. Jamkesmas and BLT have similar baseline targeting errors with, respectively, leakage rates of 34% and 39% and undercoverage rates of 45% and 51%. These patterns in targeting errors align with previous research analysing the targeting performance of Indonesia's social protection programmes before establishment of the UDB (World Bank 2012).

Results presented in column 2 of table 3 show first that Raskin and Jamkesmas coverage levels decrease significantly with the UDB compared with baseline. This reduction in the number of beneficiaries automatically leads to an increase in undercoverage for both Raskin (from 11% to 54%) and Jamkesmas (from 45% to 53%). Another consequence of the expected decrease in coverage is that leakage to non-poor households is expected to decrease significantly with Raskin and Jamkesmas using the UDB. These improvements are most apparent for Raskin, where the baseline leakage of 74% is expected to decrease by 50 percentage points with the UDB. For Jamkesmas, baseline leakage rates are expected to fall from 39% to 25% with the use of the UDB, with severe leakage falling even further from 33% to 17%.

Similar patterns are observed when focusing on the 'severe' measures of undercoverage and leakage listed in table 3, which are lower across all programmes, at baseline, and with the UDB.

The difference between baseline and expected UDB errors is difficult to interpret, given the substantial change in programme coverage levels associated with the transition to using the UDB for selecting beneficiaries. It is therefore useful to keep coverage levels constant as an alternate way to assess the change in targeting performance expected from programmes that transition to using the UDB. We do this using baseline BLT 2008 coverage levels and identify households that would be eligible for a programme with such coverage based on the UDB. We choose to match BLT 2008 coverage levels because previous research (World Bank 2012) indicates that the BLT 2008 has the highest targeting accuracy among the three social programmes considered, and thus using it as a benchmark provides the strictest possible test of the UDB's performance relative to baseline.[29]

Table 3. Baseline and Expected UDB Programme Targeting Accuracy

Targeting Measures	(1) Baseline (%)	(2) Expected UDB (%)
Panel A: Raskin		
Coverage level	80	31
Leakage	74.4	23.5
Severe leakage	66.7	16.4
Undercoverage	10.9	54.0
Severe undercoverage	7.7	49.6
Panel B: Jamkesmas		
Coverage level	44	33
Leakage	38.7	24.9
Severe leakage	32.5	17.4
Undercoverage	44.9	52.6
Severe undercoverage	42.8	48.4
Panel C: BLT 2008		
Coverage level	39	39
Leakage	34.2	31.5
Severe leakage	27.0	24.0
Undercoverage	50.5	47.7
Severe undercoverage	48.1	44.2

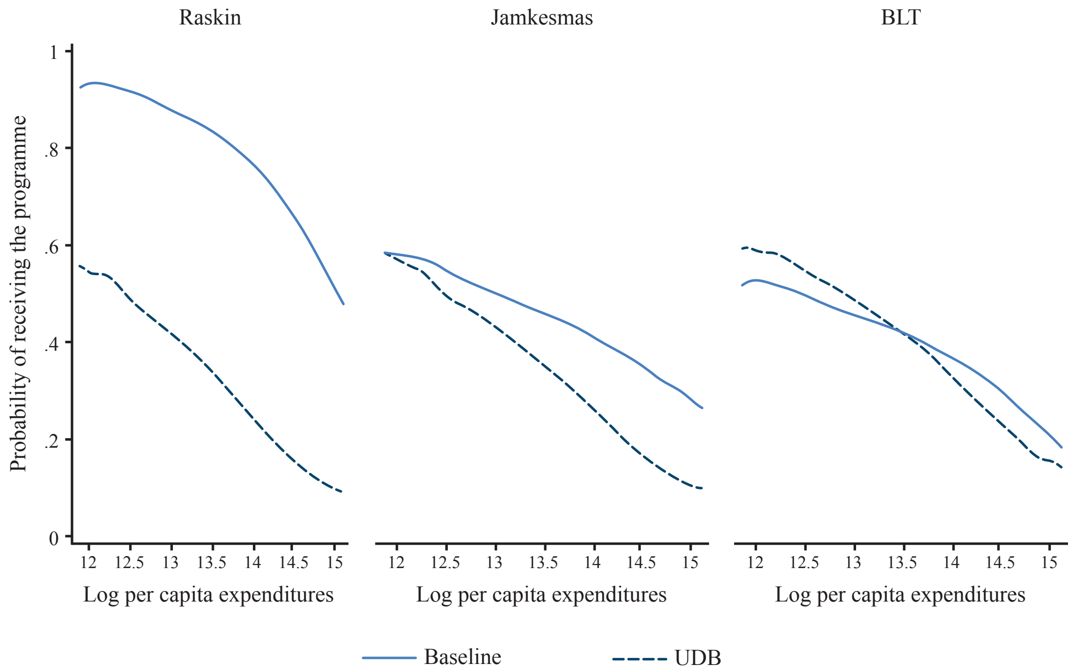
Notes: This table reports estimates of targeting errors, computed separately for 2008 Raskin, Jamkesmas, and BLT programmes. Leakage (severe leakage) captures the fraction of households with adjusted expenditures per capita at baseline above the 60th (20th) percentile of the consumption distribution that receive the given programme. Similarly, undercoverage (severe undercoverage) captures the fraction of the poorest 30% (10%) that do not receive the given programme. The definition of programme receipt varies across columns. In column 1, programme receipt is as reported by households in Suseti. In column 2, programme receipt equals one if the household's PMT score in the UDB places it within the pool of intended programme recipients. In this column, the BLT 2008 programme is based on ranking the household PMT scores and taking all households with PMT scores up to the number of households reporting BLT 2008 receipt in Suseti. This calculation is done within each of the six districts in keeping with the district-specific targeting quotas.

[29] In addition, only 43% of Suseti households are matched with the UDB, which is lower than Raskin and Jamkesmas baseline coverage levels at respectively 80% and 44%.

As shown in column 2, panel C, of table 3, holding coverage levels constant, using the UDB would reduce undercoverage and severe undercoverage of the BLT programme from 51% to 48% and from 48% to 44%, respectively. This decrease in exclusion errors further suggests that the main reason for the increase in undercoverage expected with usage of the UDB for Raskin and Jamkesmas noted earlier in this section is the concurrent decrease in their coverage levels, compared with baseline. Leakage also decreases for this simulated BLT programme from 34% to 32%. To summarise, holding (BLT 2008) coverage levels constant, the UDB is predicted to improve both undercoverage and leakage, representing a roughly 6% improvement in each of the respective errors relative to baseline.

As to distribution of programme receipt across household per capita consumption deciles, figure 2 shows that targeting for all programmes is rather progressive. At both baseline and with the UDB, a larger share of households from the poorest consumption deciles is receiving each programme, compared with households from the richest consumption deciles. The graphs confirm that the UDB has led to an improvement in the targeting performance of the three main Indonesian social assistance programmes. There is a considerable reduction in leakage with the UDB compared with baseline. The probability of receiving benefits decreases faster as per capita expenditures increase with the UDB, compared with baseline for all programmes, despite the large decrease in coverage observed for Raskin and, to a lesser extent, for Jamkesmas. At a constant coverage level (for BLT), the difference is lower but remains significant. The difference in the slopes of the lines predicting the probability of receiving any of the three programmes at baseline and with the UDB is positive and significant.[30] This implies that targeting using the UDB is more progressive than with the previous approaches to beneficiary selection used in Indonesia.

Figure 2. Programme Benefit Incidence: Baseline and UDB



Notes: This figure shows the probability of receiving each programme at baseline and with the UDB as a function of adjusted per capita expenditures, estimated using local linear regressions. Baseline programme receipt and per capita expenditures are from Suseti. UDB programme receipt is based on beneficiary lists from the UDB. For BLT, UDB programme receipt is based on ranking household PMT scores and taking all households with PMT scores up to the number of households reporting BLT 2008 receipt in Suseti.

[30] This is confirmed by the results of a Wald test, available upon request.

4.3 Disentangling Misenumeration and Misclassification

As described earlier, targeting errors in the UDB can be attributed to two factors: (1) misenumeration, or undercoverage of poor households during the enumeration process and (2) misclassification of households during the PMT modelling stage. This section attempts to disentangle these two sources of errors using 'reconstructed' PMT scores calculated for all households in the Suseti sample, instead of focusing only on those matched households that are actually registered in the current UDB. This permits assessment of UDB performance that would be observed if all households had been registered and scored in the UDB, rather than only surveying households expected to be poor (based on the pre-listings from poverty mapping and consultation with community members). Simulating outcomes under this census scenario makes it possible to remove errors, as poor households are not enumerated, and instead to isolate the role of the PMT process in contributing to targeting errors.

We reconstruct PMT scores for all households in the Suseti sample by applying the PMT algorithms used by UDB planners to the underlying PMT variables collected from each household in Suseti. We then calculate targeting errors by comparing programme eligibility status (based on the reconstructed PMT scores and on UDB-based coverage levels; see column 2, table 3) against household expenditure rankings (from Suseti).

Table 4 shows the improvement in targeting errors expected under this full census scenario relative to the UDB targeting errors presented earlier. More specifically, the measures presented in table 4 are computed as the difference between the targeting errors presented in columns 1 and 2 of table 3 and the ones obtained when assigning programme receipt to all households with reconstructed PMT scores below the given programme eligibility threshold, as a share of the UDB errors from table 3:

$$CP_U = \frac{U_{PMT_{UDB}} - U_{PMT_{SST}}}{U_{PMT_{UDB}}} \qquad (1)$$

Where U refers to the different measures of undercoverage and leakage used in the previous section; PMT_{UDB} refers to household eligibility status based on actual PMT scores from the UDB; and PMT_{SST} refers to eligibility status based on PMT scores reconstructed using the underlying PMT variables from SUSETI.

A negative (positive) sign indicates a decrease (increase) in targeting errors if all households had been registered in the UDB. Both leakage and undercoverage rates in the UDB are projected to improve under this scenario across all programmes by 11%–17% and 13%–17%, respectively. The improvements are even more striking for severe leakage and particularly severe undercoverage as gains in the latter range 27%–36% across programmes. In other words, it appears that expanding the number of households enumerated in the national targeting survey holds significant potential for improving targeting outcomes, particularly by reducing exclusion of the poor.

Figure 3 includes the predicted probability of receiving programme benefits based on the PMT scores reconstructed for all households using the data collected in Suseti in the comparison of benefit incidence between baseline and UDB-based (for households registered in the UDB) programme receipt presented in figure 2. In line with results from table 4, households from the poorest three consumption deciles have a higher probability of receiving programme benefits when considering PMT-specific predictions for all Suseti households, as opposed to UDB households only. The census scenario (reconstructed

PMT scores) also leads to some improvements in leakage, as shown by the lower programme receipt probability for households from the richest half of the population.

We use the results of this exercise to demonstrate the cost-effectiveness of expanding enumeration to cover the full population. It is estimated that, under a census scenario, households from the poorest three deciles would be more likely to receive Raskin and Jamkesmas by about 6 percentage points and more likely to receive BLT by about 8 percentage points. From this, we extrapolate that an additional 1.1 million households from the poorest three deciles would receive benefits from these three programmes under a full enumeration scenario. Benefit levels of Raskin, Jamkesmas, and BLT amount annually to a total of Rp 2.4 million (about US$200) per household or Rp 1.2 million, 0.96 million, and 0.2 million respectively.[31] Assuming that the unit cost of surveying the remaining 60% of the population would be similar to the one incurred in establishing the UDB[32]—about Rp 25,000 (US$2) per household for a survey done during a three-year period—it follows that surveying the full population would cost about 11% of the value of additional benefits that would be received annually by households from the poorest three deciles.

Table 4. Expected Improvement in Targeting Accuracy with Full Census Enumeration

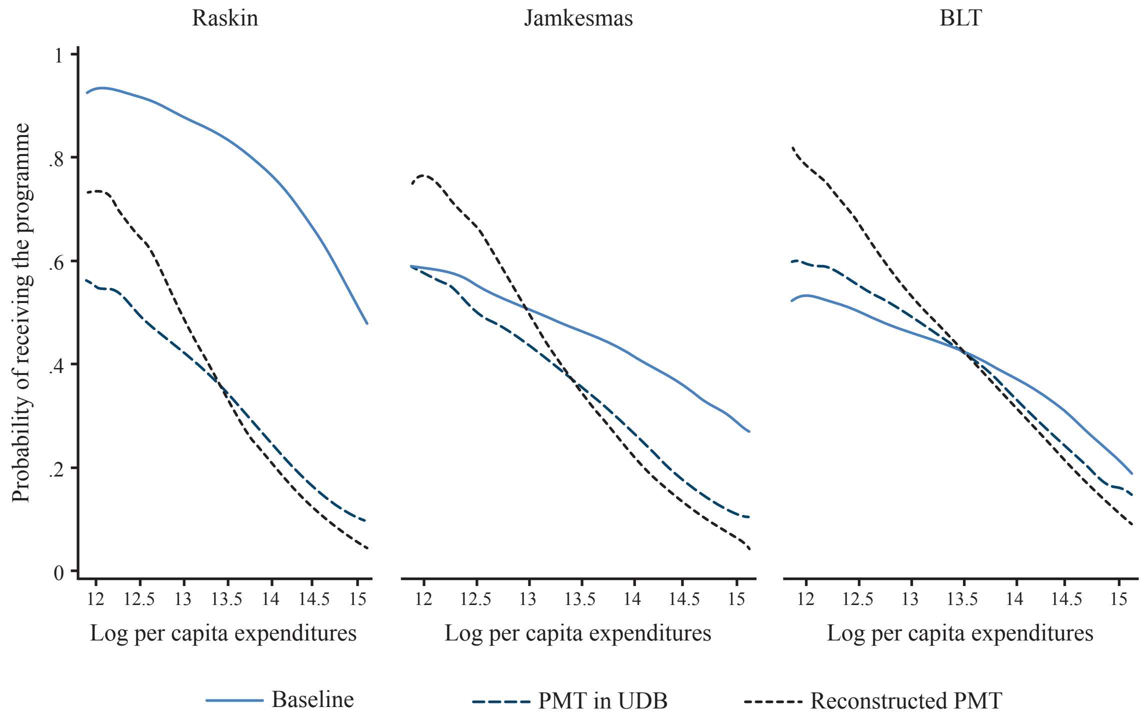
Targeting Metrics	Expected Change in Targeting Error, Compared to UDB (%)
Panel A: Raskin	
Leakage	–16.6
Severe leakage	–19.5
Undercoverage	–13.0
Severe undercoverage	–27.2
Panel B: Jamkesmas	
Leakage	–16.1
Severe leakage	–18.4
Undercoverage	–14.1
Severe undercoverage	–30.8
Panel C: BLT 2008	
Leakage	–11.4
Severe leakage	–18.8
Undercoverage	–16.8
Severe undercoverage	–35.5

Notes: This table reports estimates of UDB targeting errors based on reconstructed PMT scores for all Suseti households (i.e., simulating a scenario of full census enumeration). Programme receipt equals one for all households with reconstructed PMT score rankings that fall below the number of households eligible to receive programmes based on the UDB. The BLT 2008 eligibility is based on the same procedure as in table 3, that is, ranking the household PMT scores and taking all households with PMT scores up to the number of households reporting BLT 2008 receipt in Suseti.

[31] Raskin benefits are valued at Rp 90,000 per household per month, based on provision of 15 kilograms of rice per month at a subsidy equivalent to about Rp 6,000 per kilogram compared to the market price. For Jamkesmas, the value of the premium of the newly established national health insurance, which is currently paid for by the government for households from the poorest 40%, is used; this amounts to about Rp 80,000 per month for a household of four members. For BLT, the value of benefits provided in 2013—Rp 600,000 per household per year—is divided by three, assuming that this temporary compensation programme is only implemented once during a three-year period. In the past, BLT provided households with Rp 1.2 million (2005) and Rp 900,000 (2008).

[32] Based on the 2010 Population Census, there are a total of about 61.2 million households.

Figure 3. Programme Benefit Incidence: Baseline, UDB and Reconstructed PMT Scores



Notes: Baseline programme receipt and per capita expenditures are from Suseti. 'PMT in UDB' refers to Suseti households matched with the UDB and ranked using their PMT scores from the UDB. 'Reconstructed PMT' refers to all households in the Suseti sample ranked according to their PMT score reconstructed using the underlying PMT variables from Suseti. Similar results are obtained when also using the reconstructed PMT scores for households matched with the UDB.

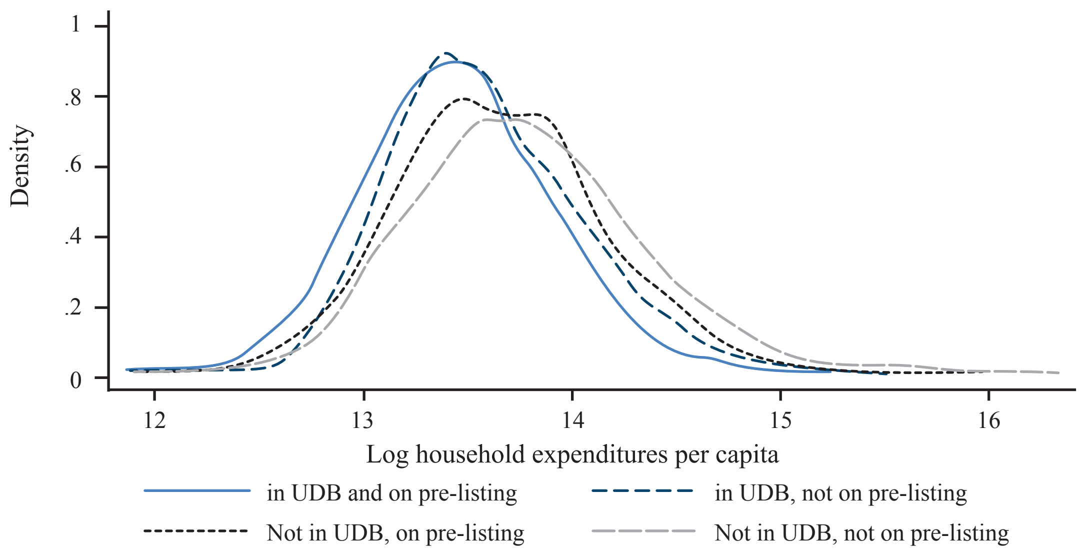
5. Towards Explaining Targeting Performance

This section explores individual- and village-level factors that are associated with misenumeration[33] and PMT misclassification in order to gain deeper insight into targeting processes and effectiveness. First, as noted earlier, during the enumeration process, households have been removed and added to the pre-listing of households to be surveyed, which was constructed using the 2010 Population Census and Elbers et al. (2003) poverty mapping methodology. Misenumeration may occur as a result of the addition and removal of households if households added (removed) have on average a higher (lower) socioeconomic status than those that end up being registered in the UDB. Second, during the PMT modelling process, a limited number of observable household characteristics were used to predict welfare levels. Misclassification may occur if these observable characteristics only capture a limited share of the relevant overall variation in household welfare.

5.1 Unpacking the Enumeration Process

This section considers which of the different methods used for registering households in the UDB led to surveying poorer households. In addition to the initial roster of households to be surveyed (pre-listing), community suggestions were used to identify additional poor households during the data collection. We also match Suseti with the enumeration pre-listings and identify 1,048 households removed from these pre-listings because they were considered to be rich and therefore not registered in the UDB. Figure 4 shows that the consumption distribution of UDB households surveyed with the pre-listing is slightly more to the left (poorer) compared with that of UDB households identified through community suggestions ('in UDB, not on pre-listing'), and both of these distributions are poorer compared with households not in the UDB, in line with figures 1a and 1b. Households that had been removed from the survey enumeration pre-listing and therefore not registered in the UDB have a consumption distribution similar to other households not registered in the UDB.

Figure 4. Distribution of per Capita Expenditures, by Registration Channel



[33] Note that the term 'misenumeration' here comprises all possible implementation errors that occurred during the process of registering households in the UDB. We are not able to distinguish fully between errors caused by the poverty map and those caused by suggestions from local communities.

To analyse additional factors that predict household registration in the UDB or having been removed from the enumeration pre-listing for being considered rich (see section 2.1), we estimate the following Probit models:

$$\Pr(UDB_h = 1 \mid PCE_h, \boldsymbol{X}_h, \boldsymbol{Z}_{vh}) = \Phi(\alpha_1 + \beta_1 \ln(PCE_h) + \boldsymbol{X}_h^{'}\boldsymbol{\gamma_1} + \boldsymbol{Z}_{vh}^{'}\boldsymbol{\delta_1}) \quad (2)$$

$$\Pr(Removed_h = 1 \mid PCE_h, \boldsymbol{X}_h, \boldsymbol{Z}_{vh}) = \Phi(\alpha_2 + \beta_2 \ln(PCE_h) + \boldsymbol{X}_h^{'}\boldsymbol{\gamma_2} + \boldsymbol{Z}_{vh}^{'}\boldsymbol{\delta_2}), \quad (3)$$

Where UDB_h is equal to one if household h is registered in the UDB, zero otherwise; and $Removed_h$ is equal to one if household h has been removed from the enumeration pre-listing, zero otherwise.

The set of variables X and Z are selected to reflect household- and community-level characteristics that are not included in the process of determining enumeration quotas or the calculation of PMT scores but may affect misenumeration through their correlation with household welfare and/or local implementation features.[34] At the household level, we consider several factors associated with household 'hidden assets'[35] as relevant to the enumeration process: exposure to shocks, and social connectedness and position within the community. Controlling for expenditure levels, we expect households owning hidden assets to be less likely to be registered in the UDB and more likely to have been removed from the enumeration pre-listing. On the contrary, -households that experience shocks, have more social connections, and are considered poor within their community should be more likely to be registered in the UDB. At the community level, we consider indicators of the relative economic status of the community, as well as the potential for elite capture, proxied by the characteristics of community (neighbourhood) heads and the remoteness of the village. We expect households living in relatively poorer communities that are less vulnerable to elite capture to be more likely to be registered in the UDB. It should be emphasised that these regressions are merely conditional correlations, and we do not intend to assign a causal interpretation.

Results for equation (2) are presented in columns 1 and 2 in table 5, whereas results for equation (3) are presented in columns 3 and 4 in table 5. The negative and significant coefficient associated with household per capita consumption aligns with the findings of figure 1b. Interestingly, per capita consumption has no significant correlation with the probability of removal from the enumeration pre-listing because of being 'rich'. This is consistent with recent evidence suggesting that the definition of being poor used by communities may only partially be correlated with household per capita consumption (Alatas et al. 2012). Alternatively, it could indicate a certain degree of elite capture over the process of determining which households are registered in the UDB.

Conditional on their level of consumption, households that own partially hidden assets, such as land or gold, are less likely to be registered in the UDB and more likely to be removed from the pre-list, suggesting that communities may not have abused this possibility to remove households. This is consistent with the argument that local communities have better information on the socioeconomic status of their members (Dreze and Sen 1989).

[34] Table A1 in annex lists all variables and their summary statistics.

[35] The term 'hidden assets' is used to refer to assets that are difficult for enumerators to observe directly and therefore more subject to misreporting. It is commonly advocated to avoid using such easily manipulable indicators for estimating PMT scores, due to the increased probability of misreporting, especially when respondents are aware that the survey is being conducted for the purpose of selecting beneficiaries for social assistance programmes. In Colombia, Camacho and Conover (2011) provide evidence that, when PMT formulas become known, there is an increase in misreporting to increase one's chances of receiving programme benefits.

Controlling for socioeconomic status, several proxies for social connectedness are associated with a higher probability of registration in the UDB. For example, migration is associated with a higher chance of registration in the UDB; two likely explanations are that (1) migration is a way for households to cope with economic hardship and hence these households are relatively poor and (2) migrants must register with the village head, suggesting that these households and those that have family connections in the neighbourhood (which also increase the probability of being in the UDB) are known to community leaders and therefore less likely to be 'missed' during the enumeration process, conditional on their expenditure levels. Meanwhile, proxies for household position within the community, in particular the receipt of assistance from the community, are also associated with a higher probability of registration in the UDB. Interestingly, receiving nongovernmental assistance is associated with a higher probability of removal from the enumeration pre-listing and also of ultimate inclusion in the UDB. Receipt of *zakat*[36], however, is associated with a higher probability of registration in the UDB and a lower probability of removal from the pre-listing. Again, this suggests the coexistence of different definitions of poverty used by communities (Alatas et al. 2012). There may also be a concern for fairness within communities; as a result, households that have access to alternative forms of support when facing hardship may be more likely to be removed from the pre-listing.

At the community level, having an RT head who considers the district to be poorer than other districts is associated with a higher probability of enumeration. This aligns with findings of SMERU (2012) indicating that community leaders are reluctant to survey a high number of households and particularly those not considered to be poor, as this would raise households' expectations on receiving programme benefits. Among indicators of the potential for elite capture, households in communities where the RT head declares that s/he knows each community member very well have a lower probability of removal from the enumeration pre-listing. Village remoteness is negatively associated with registration in the UDB and positively with removal from enumeration pre-listings, all else being equal. These areas may be more difficult or more costly for enumerators to reach, and supervision of enumerators may be lacking in these areas, potentially leading to local leaders that have more leeway in removing people from the pre-listing (even if they deserve to be registered in the UDB).

[36] The reception of *zakat* is also included in the nongovernmental assistance dummy (and in the annual per capita value), which also comprises assistance received from religious or political institutions, as well as from national and international nongovernmental organisations, firms/corporations, and other private donors. Assistance received in response to disaster is excluded.

Table 5. Hidden Household- and Village-Level Characteristics Associated with Registration in the UDB

Variables	Pr (in the UDB)		Pr (Household removed from PL[a])	
	1	2	3	4
Log per capita expenditures	–0.512***	–0.501***	–0.029	–0.019
	(0.051)	(0.052)	(0.056)	(0.058)
Asset: Land	–0.162***	–0.173***	0.277***	0.264***
	(0.061)	(0.058)	(0.075)	(0.077)
Asset: Jewellery or gold/savings ≥ Rp 500,000	–0.346***	–0.334***	0.117**	0.124**
	(0.038)	(0.037)	(0.050)	(0.049)
Asset: Livestock with value ≥ Rp 500,000	–0.028	–0.047	0.272***	0.249***
	(0.055)	(0.054)	(0.051)	(0.052)
Household has experienced a shock in past year	0.046	0.031	0.070*	0.066
	(0.048)	(0.047)	(0.038)	(0.041)
Nb of family members living in the same RW[a]/RT	0.022**	0.016*	0.012	0.009
	(0.010)	(0.010)	(0.010)	(0.011)
At least one household member has migrated	0.085**	0.095**	0.030	0.037
	(0.042)	(0.040)	(0.040)	(0.040)
At least one household member participates in community group	0.024	0.035	0.009	0.004
	(0.047)	(0.050)	(0.072)	(0.070)
Assistance received from nongovernmental institution in past year	0.473*	0.384	0.784**	0.720**
	(0.256)	(0.253)	(0.335)	(0.340)
Zakat was received in past year	0.435***	0.462***	–0.214***	–0.218***
	(0.044)	(0.041)	(0.061)	(0.061)
Log per capita value of total nongovernmental assistance, past year	–0.042	–0.032	–0.087**	–0.077**
	(0.028)	(0.027)	(0.035)	(0.035)
UDB enumeration quotas, percentage of village population		0.921***		0.674***
		(0.171)		(0.163)
Village is much or slightly poorer than other villages in district		–0.014		–0.083
		(0.079)		(0.087)
Village has similar income level as other villages in district		–0.059		–0.079
		(0.081)		(0.083)
District is much or slightly poorer than other districts		0.092*		–0.070
		(0.052)		(0.043)
(Log) distance between village and district capital		–0.061		–0.093*
		(0.052)		(0.056)
RT head knows each community member very well		–0.087		–0.009
		(0.061)		(0.068)
RT head is elected		–0.110*		0.125**
		(0.056)		(0.059)
Constant	7.045***	6.823***	–1.098	–1.969**
	(0.671)	(0.779)	(0.763)	(0.808)
Observations	5,680	5,680	5,680	5,680
Pseudo R-squared	0.113	0.129	0.0557	0.0673

[a] PL: pre-listing; RW: *rukun warga* (community association).

Notes: This table reports the results of Probit estimates of the probability of registration in the UDB—columns 1 and 2—and of being removed from the enumeration pre-listing for being considered rich - columns 3 and 4. All regressions include district fixed effects, and standard errors are clustered at the subdistrict level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Unpacking the PMT Classification

This section examines the determinants of the gap between a household's actual per capita consumption and its PMT score, which indicates the extent of targeting errors due to PMT misclassification. In particular, we estimate the following two regressions:

$$\ln\left(\frac{PCE_h}{PMT\_UDB_h}\right) = \alpha_1 + \boldsymbol{X}'_h\boldsymbol{\gamma}^1_{UDB} + \boldsymbol{Z}'_{vh}\boldsymbol{\delta}^1_{UDB} + \varepsilon^1_{vh} \quad (4)$$

$$\ln\left(\frac{PCE_h}{PMT\_SST_h}\right) = \alpha_2 + \boldsymbol{X}'_h\boldsymbol{\gamma}^2_{SST} + \boldsymbol{Z}'_{vh}\boldsymbol{\delta}^2_{SST} + \varepsilon^2_{vh} \quad (5)$$

The more positive the dependent variable is for a household, the greater the extent that the PMT score underestimates actual consumption (i.e., potential inclusion error). Conversely, the more negative $\ln\left(\frac{PCE_h}{PMT_h}\right)$ is, the greater the extent that the PMT score overestimates actual consumption (i.e., potential exclusion error). The difference between equations (4) and (5) is similar to the difference between the targeting error results presented in tables 3 and 4. Equation (4) estimates the correlation between misclassification and household and community characteristics conditional on actual registration in the UDB and uses household PMT scores from the UDB. By relaxing this sample restriction and considering all Suseti households based on their reconstructed PMT scores in equation (5), we are able to isolate the influence of the PMT process. Results for equation (4) are presented in columns 1 and 2 of table 6, and results for equation (5) are presented in columns 3 and 4 of table 6.

Across all specifications, ownership of hidden assets of a value equal to or above Rp 500,000 (about US$40) is associated with underprediction of household consumption by the PMT formulas. All else being equal, actual expenditures of households owning such assets are between 6% and 14% higher on average than their estimated PMT scores. This is relatively unsurprising. However, use of these partially hidden assets is not recommended in PMT-based scoring, because they are not easily verifiable and therefore more likely to be manipulated by households. The occurrence of a shock at the household level in the past year is also significantly associated with potential leakage; actual per capita expenditures were on average 4% higher than PMT scores, conditional on registration in the UDB. This can be considered an 'acceptable' inclusion error, as shocks may render these households vulnerable to being poor. Moreover, receiving nongovernmental assistance and/or *zakat* is associated with having a PMT score or predicted welfare level between 10% and 50% higher than actual per capita expenditures. This further suggests that communities use a different definition of poverty.

Table 6. Hidden Household- and Village-Level Characteristics Associated with PMT Classification Errors

Variables	OLS: Log(PCE/PMT_UDB) 1	2	OLS: Log(PCE/PMT_SST) 3	4
Asset: Land	0.033 (0.028)	0.028 (0.027)	0.013 (0.018)	0.014 (0.018)
Asset: Jewellery or gold/savings ≥ Rp 500,000	0.110*** (0.023)	0.106*** (0.023)	0.137*** (0.015)	0.136*** (0.015)
Asset: Livestock with value ≥ Rp 500,000	0.062** (0.028)	0.058** (0.029)	0.079*** (0.017)	0.079*** (0.017)
Household experienced a shock in past year	0.044* (0.022)	0.045** (0.022)	0.019 (0.017)	0.019 (0.016)
Nb of family members living in the same RW[a]/RT	0.007 (0.005)	0.006 (0.005)	0.006** (0.003)	0.006** (0.003)
At least one household member migrated	0.023 (0.020)	0.025 (0.020)	0.004 (0.013)	0.004 (0.012)
At least one household member participates in community group	0.038 (0.030)	0.044 (0.030)	0.032* (0.019)	0.034* (0.019)
Assistance received from nongovernmental institution in past year	–0.510*** (0.130)	–0.506*** (0.126)	–0.506*** (0.074)	–0.501*** (0.072)
Zakat received in past year	–0.107*** (0.026)	–0.108*** (0.026)	–0.114*** (0.016)	–0.114*** (0.016)
Log per capita value of total nongovernmental assistance, past year	0.057*** (0.015)	0.058*** (0.014)	0.052*** (0.008)	0.051*** (0.008)
UDB enumeration quotas, percentage of village population		–0.004 (0.074)		–0.040 (0.051)
Village is much or slightly poorer than other villages in district		0.049 (0.035)		–0.002 (0.026)
Village has similar income level as other villages in district		–0.026 (0.032)		–0.017 (0.025)
District is much or slightly poorer than other districts		–0.049* (0.028)		–0.022 (0.017)
RT head knows each community member very well		–0.017 (0.025)		–0.037** (0.014)
RT head is elected		–0.071*** (0.023)		–0.032** (0.014)
Log distance village and district capital		0.001 (0.032)		0.004 (0.019)
Constant	0.288*** (0.064)	0.308** (0.151)	0.279*** (0.040)	0.328*** (0.098)
Observations	2,443	2,443	5,680	5,680
R-squared	0.128	0.137	0.135	0.138
Adjusted R-squared	0.123	0.129	0.132	0.134

[a] RW: *rukun warga* (community association)

Notes: This table reports the results of OLS estimates of the logarithm of the ratio PCE/PMT. All regressions include district fixed effects, and standard errors are clustered at the subdistrict level. Columns 1 and 2 are conditional on registration in the UDB and use the actual PMT score from the UDB. Columns 3 and 4 are unconditional on registration in the UDB, and are based on the PMT score reconstructed using Suseti variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Turning to community-level characteristics, conditional on registration in the UDB, the RT head considering the district to be poorer than other districts is associated with exclusion (i.e., having an actual per capita consumption level about 5% lower than predicted by the PMT). This is consistent with the fact that OLS-based PMT ranking is less accurate at the left of the consumption distribution (Grosh and Baker 1995), making the distinction among relatively poor households more difficult.[37] Also consistent with this premise is the correlation of the RT head election with a PMT score higher than actual consumption, both conditional and unconditional on registration in the UDB. Indeed, although each district government has produced specific regulations regarding the organisation of neighbourhood associations since 1999 (Kurasawa 2009), RT heads are more often elected in rural areas, which are characterised by a higher poverty incidence.

[37] Part of the literature advocates using alternative statistical approaches, given the inaccuracy of OLS-based PMT estimations at the bottom of the distribution. Muller and Bibi (2010), for instance, provide evidence that censored quantile regressions anchored on the first decile minimise undercoverage.

6. Concluding Remarks

This paper evaluates the effectiveness of the world's largest targeting system for delivering social programme benefits. We show that use of the UDB in Indonesia can be expected to significantly reduce leakage of benefits to non-poor households. However, undercoverage remains relatively high, due largely to the difficulties of enumerating the right households for inclusion in the UDB. We indeed predict a decrease in undercoverage by about 30% under a simulation that considers enumerating and estimating PMT scores for all households (as in a census), compared with focusing only on households that have been registered in the UDB. This is the first paper to identify the relative importance of enumeration versus PMT errors in determining the overall effectiveness of a large-scale targeting system.

About 25 million households were surveyed for the UDB using a combination of poverty maps and suggestions from communities at a relatively low cost of around US$2 per household. Based on the finding that targeting accuracy may be improved through more extensive coverage of households, we propose two practical strategies to achieve this for Indonesia's UDB, as well as for other countries developing similar national targeting registries.

The first proposed strategy is to increase the number of households enumerated in the national targeting registry survey. One option is to conduct a census of the full population (rather than only select households expected to be poor), as we simulate in this paper. Although it is commonly argued that it is too expensive to visit the entire population, we find that surveying the remaining 60% of the population would (only) cost about 11% of the value of additional benefits that would be received by households from the poorest three deciles nationally, assuming a one-third improvement in undercoverage and that the data collected are used for three years. If conducting a full census is nevertheless considered cost prohibitive, a related option would be to first identify the poorest areas based on small-area poverty maps and then survey all households in these geographic areas.

The second proposed strategy, which could be combined with the first, is to transform the household targeting system registration into a more open process in order to allow greater entry. Other countries, such as Colombia and the Philippines, combine a complete census in the poorest areas with on-demand applications (also referred to as self-targeting) in other areas, in an attempt to survey as many poor households as possible while maintaining relatively low total registration costs. In an on-demand approach, households that consider themselves eligible for a given programme are allowed to apply for inclusion in the registry. In a randomised pilot experiment in Indonesia, Alatas et al. (2013b) found that self-targeting leads to similar undercoverage as full enumeration at a lower overall cost, because it surveys fewer households. However, further research is needed to assess the cost-effectiveness of these different strategies, especially given evidence from this study that self-targeting excludes some of the poorest households, which do not apply—and leads to higher costs incurred directly by households (Alatas et al. 2013b).

Either of these strategies could be further bolstered with a greater focus on improving the cost-effectiveness of the household registration process. For instance, one cost-effective alternative may be to shorten the targeting questionnaire to allow a larger number of households to be surveyed at a lower cost, which might not necessarily come at the expense of targeting accuracy. Indeed, Bah (2013) showed that increasing the number of indicators included in a PMT formula from 10 to 30 does not significantly increase the accuracy of predicted household poverty levels nor reduce targeting errors.[38]

Furthermore, the targeting accuracy results in this paper are based on the assumption of perfect (or strong) correspondence between the beneficiary lists from the UDB registry and the households who actually end up receiving social programme benefits. A growing literature examining the political economy of targeting has provided evidence that, in practice, official beneficiary lists may be modified in the field, which may positively or negatively affect targeting outcomes.[39] In Indonesia, past research suggests some departures although overall adherence to official beneficiary lists has typically been quite high (World Bank 2012). Such targeting rule violations may prove beneficial if they allow the community to exert their greater ability to identify the very poor (Alatas et al. 2012) or if the capture of programme benefits by local elites is limited or generates relatively small welfare losses (Alatas et al. 2013a). Future research should combine the methods for evaluating targeting effectiveness that we advocate in this paper with an assessment of eligibility adherence in the field to identify which effects prevail overall.

[38] Dreze and Khera (2010) go even further by proposing the use of simplified targeting criteria so that "every household can attribute its inclusion in, or exclusion from, the list to a single criterion". Results from Niehaus and Atanassova (2013) justify this argument: increasing the number of poverty indicators used to assess household socioeconomic status can have adverse effects in terms of targeting outcomes as it makes eligibility less transparent and therefore more subject to manipulation by corrupt agents at the local level.

[39] Camacho and Conover (2011) identify manipulation of eligibility scores by local officials, especially around the time of local elections in Colombia. In the case of India's BPL cards, Niehaus and Atanassova (2013) provide evidence of targeting rule violations by local officials that are due to corrupt behaviour. They argue that the addition of poverty indicators into targeting formulas undermined targeting effectiveness. As a result, BPL's 'de facto' allocation is much less progressive than the 'de jure' allocation, as the use of more poverty indicators makes eligibility less transparent and thereby facilitates violations of the official rules.

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Appendix

Table A1: List of Household- and Community-Level Explanatory Variables

Variables	Mean	SD	Min	Max
Panel A: Household-Level Variables				
Hidden assets				
Asset: Land.	85.34			
Asset: Jewellery or gold/savings ≥ Rp 500,000.	44.30			
Asset: Livestock with value ≥ Rp 500,000.	22.26			
Exposure to shock				
Household experienced shock in past year.	24.08			
Social connectedness				
Nb of family members living in the same RWa/RT.	2.36	2.26	0.00	20.00
At least one household member migrated.	40.87			
At least one household member participates in community group.	78.85			
Position within the community				
Assistance from nongovernmental institution in past year.	86.73			
Reception of *zakat*, past year.	34.95			
(Log) per capita value of total nongovernmental assistance in past year.	8.09	3.31	0.00	15.43
Panel B: Community-Level Variables				
Community relative economic status				
UDB enumeration quotas, percentage of village population.	0.51	0.21	0.04	0.99
Village is much or slightly poorer than other villages in district.	48.24			
Village has similar income level as other villages in district.	39.05			
District is much or slightly poorer than other districts.	50.07			
Potential for elite capture				
(Log) distance between village and district capital.	3.58	0.59	1.10	5.25
RT head knows each community member very well.	72.91			
RT head is elected.	53.29			

a RW: *rukun warga* (community association).
Notes: At the household level, partially hidden assets considered include land, jewellery, savings, and livestock of a value larger than Rp 500,000 (about US$40). The shock variable is a dummy equal to one if the household has experienced the death or serious illness of a household member, loss of employment, harvest or business failure, or a natural disaster between the baseline and end-line Suseti surveys (i.e., between January 2011 and February 2012). Social connectedness variables include the number of other family members living in the same neighbourhood, as well as dummy variables for whether at least one household member migrated and participates in a community group. Variables translating household's socioeconomic position as viewed by the community include the reception of assistance from the nongovernmental institutions and its per capita value, and the reception of *zakat* (religious assistance distributed through the mosque). The reception of *zakat* is also included in the nongovernmental assistance dummy (and in the annual per capita value), which excludes disaster-related assistance but includes assistance received from religious or political institutions as well as from national and international nongovernmental organisations, firms/corporations, and other private donors. At the community level, indicators of the relative position of the community include the UDB enumeration quotas as a share of total village population, as well as RT heads' perceptions on whether the village in which the neighbourhood is located is poorer or similar to other villages within the district, and whether the district is poorer than other districts in the province. Indicators of the potential or elite capture include the (logarithm) of the distance between the village and the district capital, from the 2011 Village Census survey (*Potensi Desa* or PODES) conducted in Indonesia every three years, and dummies equal to one if the RT head is elected and if he/she declares that s/he knows each member of the community very well.

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Centralised targeting registries are increasingly used to allocate social assistance benefits in developing countries. This paper provides the first attempt to identify the relative importance of two key design issues for targeting accuracy: (1) which households to survey for inclusion in the targeting registry and (2) how to rank surveyed households. We evaluate the performance of Indonesia's Unified Database for Social Protection Programmes (UDB), the largest targeting registry in the world, which is used to provide social assistance to more than 25 million households. Linking administrative data with an independent household survey, we find that the UDB system is more progressive than previous targeting approaches used in Indonesia, leading to a decrease in benefit leakage to non-poor households. However, if poor households are not surveyed in the first place, even a perfect ranking method cannot prevent their exclusion. Under a simulation that considers enumerating and estimating proxy-means testing (PMT) scores for all households (as in a census), we estimate a one-third decrease in undercoverage compared to focusing on households that have been registered in the UDB. Investigating household- and community-level correlates of misenumeration and misclassification, we find evidence that local communities use different definitions of poverty and have better information on the welfare status of their members.

TIM NASIONAL PERCEPATAN PENANGGULANGAN KEMISKINAN (TNP2K)

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