Finding the Poor vs. Measuring their Poverty: Exploring the Drivers of Targeting Effectiveness in Indonesia[*]

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Abstract

Centralized 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: (i) which households to survey for inclusion in the registry and (ii) how to rank surveyed households. We evaluate Indonesia's Unified Database for Social Protection Programs (UDB), among the largest targeting registries in the world, used to provide social assistance to over 25 million households. Linking administrative data with an independent household survey, we find that the UDB system is more progressive than previous, program-specific targeting approaches. However, simulating an alternative targeting system based on enumerating all households, we find a one-third reduction in undercoverage of the poor compared to focusing on households registered in the UDB. Overall, we identify large gains in targeting performance from improving the initial registration stage relative to the ranking stage.

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1 Introduction

Social assistance programs targeted to low-income groups cover nearly two billion people in developing countries (Honorati et al., 2015). Identifying and reaching the intended beneficiaries of these programs can be challenging, especially where a large part of the population works in the informal sector and there are no official income registries. A number of targeting methods have been developed to address these challenges.[1] Traditionally, each program has its own method to select recipients depending on its implementing agency, budget, and benefit package.

In recent years, an increasing number of low- and middle-income countries are moving from fragmented program-specific targeting mechanisms to a single household targeting registry meant to select recipients of multiple social assistance programs often with different eligibility rules. Honorati et al. (2015) report that single registries for social safety nets are fully operational or are being developed in 92 developing countries.[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.[3] This information is then used to determine eligibility, most commonly based on proxy-means testing (PMT).[4]

This paper aims to identify general strategies for improving targeting effectiveness in these new unified registries by evaluating the performance of one of the world's largest single registries developed recently in Indonesia. Established in 2012, the Unified Database for Social Protection Programs (UDB) is intended to cover the poorest 40 percent of the Indonesian population. Over 25 million households have been registered in the UDB using a novel approach based on (i) a pre-listing of households to be surveyed, constructed through census-based poverty mapping (Elbers et al., 2003), and (ii) suggestions from local communities. These households were subsequently ranked by their predicted welfare status estimated using district-specific PMT scores.[5] The government has used the UDB to deliver over US$ 4 billion annually (IDR 43 trillion) in central government social assistance to date. This includes two of the country's largest social assistance programs that are the focus of this paper: a health insurance

[1] Targeting commonly relies on individual assessments (often using means- or proxy-means-testing), broad categorical eligibility (demographic or geographic targeting), self-selection, or some combination therein (see Coady et al., 2004, for a survey). A rich literature on optimal targeting finds that no method clearly dominates in terms of its ability to accurately identify the poorest (e.g., Coady et al., 2004; Banerjee et al, 2007; Coady and Parker, 2009; Alatas et al., 2012, 2013; Karlan and Thuysbaert, forthcoming).

[2] As argued by Grosh et al. (2008), "a good household targeting system may be complex to develop, but can be used for many programs […]. The shared overhead is not only efficient, but can lead to a more coherent overall social policy." Examples of countries currently using single targeting registries include Brazil, Chile, Colombia, India, Mexico and the 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 to 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 to the full population, in order to limit costs.

[4] PMT scores are constructed on the basis of 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 programs to the extent that they are sufficiently accurate.

[5] 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.

program (known by its Indonesian acronym, *Jamkesmas*) and an unconditional cash transfer program (known by its Indonesian acronym, BLT).[6]

Before the establishment of the UDB, beneficiaries of these programs were selected using ad hoc targeting approaches. In practice, community leaders had a strong influence in determining beneficiaries. Jamkesmas relied on a form of self-targeting through the use of a poverty statement issued by local leaders, and BLT on a PMT-based ranking of households designated by community leaders (World Bank, 2012). This diversity of targeting methods used by programs having similar targeting goals is common in developing countries. We use this variation across programs to assess the expected change in targeting accuracy when moving to a single, unified targeting system. We follow the literature in assessing targeting accuracy based on two key measures: *leakage* (or inclusion error), when non-intended beneficiaries receive program benefits, and *undercoverage* (or exclusion error), when intended beneficiaries do not receive program benefits (Cornia and Stewart, 1995).

Our analysis proceeds in two steps. First, we evaluate the targeting performance of the UDB against the performance of past approaches to beneficiary selection. We use data from an auxiliary, independent survey known as SUSETI, which we matched with UDB administrative data. Although limited in its geographic and demographic coverage, this survey allows us to provide internally valid estimates of targeting effectiveness under the old and new targeting regimes. Crucially, SUSETI records household expenditures, which are not observed in the UDB, as well as information on the receipt of Jamkesmas and BLT before the establishment of the UDB. Using this data, we investigate how the distribution of benefits within the study population changes when moving from past program-specific targeting allocations to the UDB.

We find that targeting using the UDB is more progressive than previous program-specific approaches to beneficiary selection. In particular, the UDB leads to a substantial reduction in leakage of benefits to non-poor households. For example, the proportion of the richest 40% of households receiving Jamkesmas is expected to fall from nearly 40% to 25%. These reductions in leakage have important welfare consequences as well as implications for the political economy of redistribution (see Pritchett, 2005).

However, we find more limited improvements in undercoverage that can be explained by 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 as *misenumeration* errors. The second challenge is

[6] Another major social assistance program is rice subsidy program known as *Raskin*. We do not analyze this program in the paper because its benefits are typically shared informally across beneficiary and non-beneficiary households. This introduces special challenges in assessing targeting effectiveness that are specific to Indonesia.

how to assess the eligibility of those surveyed, or how to estimate their socioeconomic status in order to rank or classify them. The main concern in this step is to minimize what we refer to as *misclassification* errors that stem from surveyed poor households being deemed ineligible and from non-poor surveyed households being wrongly classified as poor. Misenumeration and misclassification are key determinants of targeting accuracy. To date, however, little is known about the relative importance of registration and ranking in determining the accuracy of targeting registries, as most existing studies focus on errors due to misclassification.[7] Our unique combination of administrative and independent survey data allows us to compare the relative importance of these distinct errors to overall targeting accuracy.

We disentangle the contribution of the enumeration and the 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 counterfactual scenario, undercoverage of the poorest 10 percent of households falls by about one-third relative to a targeting system based only on those households actually included in the UDB. We also consider another popular policy of geographic targeting as an alternative to universal enumeration. In particular, we investigate the effectiveness of fully enumerating households in the poorest half of regions while retaining the existing enumeration approach in the remainder. This also leads to targeting improvements, albeit smaller in magnitude than with a full census scenario. In comparison to these improvements to the enumeration process, attempting to improve the ranking process through the use of additional information on ownership of valuable household assets that are difficult to observe (and not included in the UDB) yields relatively smaller improvements in targeting performance. This alternative ranking process reduces undercoverage by two to ten percent and leakage by nearly five percent.

This paper provides the first attempt to assess the relative contribution of the household registration and ranking processes to the overall accuracy of a centralized targeting registry. 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 public resources towards increasing survey coverage to minimize undercoverage of poor households in the UDB. Under certain assumptions about the generalizability of our survey sample, we show that increased enumeration costs to cover the full population in our study districts would amount to about 11 percent of the value of additional benefits that would be received annually by the poorest 30 percent of households. Our results point to the potential cost effectiveness of ensuring an adequate number of households are surveyed for inclusion in single targeting registries.

[7] One notable exception is Alatas et al. (2016), who show that self-targeting has the potential to reduce misenumeration errors at the registration stage.

Our paper contributes to the literature in public and development economics on optimal targeting of social programs. Most studies use a single survey to identify intended and actual recipients, i.e., who is poor and who is receiving government benefits. However, as argued by Coady et al. (2013), relying solely on household self-reporting of beneficiary status does not allow for a full understanding of what happens at the multiple stages of the targeting process, before benefits are delivered to households. Our findings relate to those of Coady and Parker (2009) and Coady et al. (2013), who consider a three-step, program-specific targeting process comprising information, self-selection to apply, and ranking stages. For the Indonesian targeting registry's two-step process—registration based on enumeration pre-listings complemented by community suggestions and then ranking—we find large gains in performance from improving the initial registration stage relative to the ranking stage. As a result, we are able to prioritize policy options to minimize 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 where there is considerable clustering of households around the poverty line, substantial churning in and out of poverty, and relatively limited geographic concentration of poverty. Nevertheless, we clarify how improvements in the enumeration process can lead to large gains in overall targeting effectiveness. If poor households are not enumerated in the first place, even a perfect PMT algorithm cannot prevent their exclusion.

The remainder of the paper is organized as follows. Section 2 provides background information on targeted social assistance in Indonesia, including the single registry. Section 3 presents the SUSETI survey and its features. Section 4 assesses the predicted targeting accuracy of the UDB. Section 5 explores the contributions of the registration and ranking stages to UDB accuracy. Section 6 concludes with policy recommendations.

2 Targeted Social Assistance Programs in Indonesia

In this section, we first present the two social assistance programs at the core of our analysis, focusing on their beneficiary selection mechanisms before the introduction of the Unified Database for Social Protection Programs (UDB). We then describe the two main steps in establishing the UDB, a centralized targeting registry of 25 million households ranked according to their socioeconomic status.

2.1 Social Assistance Programs

Indonesia's main social protection programs originate from the social safety nets programs that were launched in 1998 to mitigate the adverse impacts of the Asian Financial Crisis. From the beginning, these programs have adopted decentralized beneficiary selection mechanisms and relied on local leaders and service providers to fine-tune targeting (TNP2K, forthcoming).

The health fee waiver program, known as Jamkesmas, provides access to free services at public health facilities. District governments are responsible for compiling beneficiary lists based on community meetings and on local poverty indicators. This program has a self-targeting feature since households that consider themselves poor, and therefore eligible, can apply to receive a card by producing a poverty statement signed by the village head.

The unconditional cash transfer programs, known as BLT, provided temporary cash compensation to protect poor households against the shocks associated with fuel subsidy reductions implemented in 2005, 2008 and 2013.[8] Two censuses of the poor were used to identify BLT beneficiaries in 2005 and 2008. Households surveyed in these data collection efforts were identified based mainly on subjective consultations between enumerators from the Central Statistical Bureau (known as BPS) and village leaders (see, e.g., SMERU, 2006), and subsequently ranked using a simplified PMT. Registration was a problem. In the absence of pre-existing information, local leaders were left to designate who should be surveyed to be assessed for eligibility for receiving BLT benefits. As a result, the overall geographic allocation did not reflect the geographic distribution of poverty in the country. PMT-based ranking was also a problem, with the use of difficult to verify indicators such as the frequency of buying meat, eating, buying clothes, and the ability to afford medical treatment or the use of credit to meet daily needs. In practice, almost all households registered in these previous censuses of the poor were deemed eligible since too few households were surveyed in the first place (World Bank, 2012).

Previous studies provide evidence that inaccurate targeting of social protection programs was a major obstacle to effective poverty reduction policies in Indonesia. Jamkesmas and BLT were characterized by significant undercoverage of poor households and leakage to non-poor households. For example, according to World Bank (2012), only about half of the households below the poverty line received the BLT program in 2008. Moreover, fragmentation in targeting approaches induced higher program administration costs and efficiency losses. Due to the lack of a unified approach to beneficiary selection, these programs were implemented independently from one another, by different government agencies with a limited capacity to interact and to properly assess the degree of complementarity in benefits provided to specific target groups.

2.2 The Unified Database for Social Protection Programs

The UDB was established following two steps: data collection (enumeration) and PMT modeling (ranking). Hereafter, references to the "poor" ("non-poor") indicate those households in the bottom 40

[8] These cash transfer programs were designed to provide temporary compensation to protect poor households against the shocks associated with fuel subsidy reductions. See Bazzi et al. (2015) for an evaluation of the 2005 program's impact on household consumption. In 2013, the BLT program was renamed BLSM. For simplicity and since the program is still often referred to by its original name, we use the acronym "BLT" in this paper to refer to all programs.

(upper 60) percent of the consumption distribution and hence meant to be included in (excluded from) the UDB.

The data collection stage involved pre-identifying all *potentially* eligible households that should be surveyed. Building on lessons from the implementation of previous censuses of the poor, 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 was generated through a poverty mapping exercise. Second, suggestions from communities were incorporated in the field to amend and complete the pre-listing.[9]

The first step of pre-listing was intended to mitigate undercoverage that had plagued previous data collection efforts in 2005 and 2008 and to ensure that the spatial distribution of households surveyed would follow more closely the spatial distribution of poverty. A poverty mapping exercise was conducted using the Elbers et al. (2003) methodology and the 2010 Population Census to estimate household welfare (proxied by per capita consumption) for the entire population. Although the use of highly localized poverty mapping approaches for community or individual targeting is subject to important caveats given the potential for prediction error (see Elbers et al, 2007), this initial exercise was widely viewed by Indonesian policymakers as a means of limiting the scope for local leaders and enumerators to systematically distort benefits away from intended groups. Government planners estimated enumeration quotas separately for each district using consumption-based poverty lines from the July 2010 National Socioeconomic Survey (known as *Susenas*).[10] All households in each village with a predicted per capita consumption level below the enumeration quota cutoff were included on a pre-listing to be surveyed for inclusion in the UDB. Based on this exercise, about 27 million households, or 43 percent of the population were pre-listed to be surveyed for registration in the UDB.

The second step of the registration process aimed to incorporate community-led modifications of the pre-listings in the field. Nationwide, about 10.3 million households were removed from the pre-listings. The vast majority of these households, about 7.7 million, was removed based on community suggestions, as they were considered non-poor, while the remaining could not be found (e.g., due to relocation). In addition, about 8.4 million households that were initially not on the pre-listings were registered based on community suggestions. As a result, in total, about 25.2 million households, two-thirds of whom were on the enumeration pre-listings, were registered in the UDB nationally, with varying coverage across districts (TNP2K, forthcoming).

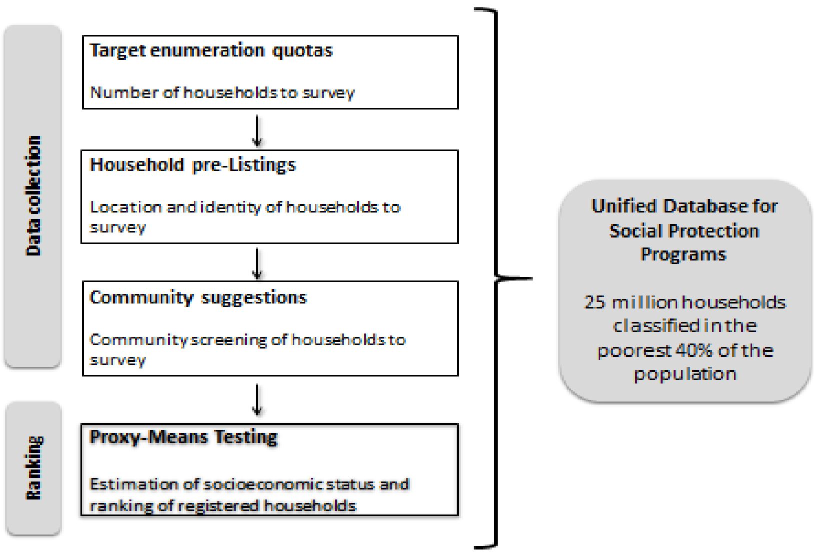
[9] Alternative approaches adopted in other countries include surveying households that request it or conducting a census in the poorest areas (e.g., Camacho and Conover, 2011; Karlan and Thuysbaert, forthcoming).
[10] Administered to a sample of households this is representative at the district level, *Susenas* includes a detailed consumption module which is used to estimate poverty lines.

Conducted in July-August 2011, the UDB registration survey comprised household-level information such as demographics, housing characteristics, sanitation, access to basic domestic energy services, and asset ownership, along with individual-level information including age, gender, schooling, and occupation. Using this data in the ranking stage, planners estimated predicted household welfare following a proxy-means testing (PMT) approach. PMT formulas were constructed based on district-specific consumption regressions to explicitly account for heterogeneity across regions. The full set of variables used in this stage is available in TNP2K (2014).

Although the PMT approach can be a cost-effective means of identifying beneficiaries of social programs, it is also prone to errors (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). The Indonesian PMT models have a predictive performance that appears similar to PMT regressions in other countries. On average, the PMT models used to rank households in the UDB have an R-squared of 0.5, a rank correlation between actual and predicted consumption of 0.67, and predicted model targeting error rates at the 40th percentile cutoff of about 30 percent (Bah, 2013). Below, we use information outside the UDB to examine the potential targeting improvements associated with increasing the predictive accuracy of the PMT.

Before proceeding, Figure 1 summarizes the multi-stage process of creating Indonesia's UDB registry of 25 million households.

Figure 1: Stages in the Development of the Unified Targeting Database



In the remainder of the paper, we investigate the overall accuracy of this unified targeting registry.

3 Empirical Strategy: Assessing Targeting Accuracy

Targeting accuracy is measured based on the discrepancy between intended and actual recipients. Researchers typically identify these discrepancies using data on household expenditures (or income) and receipt of government benefits from a single survey (see, e.g., Coady et al., 2004). Indeed, many evaluations rely on self-reported program receipt and poverty status after programs have begun.

Building upon Coady and Parker's (2009) innovative work on targeting effectiveness in Mexico, we evaluate the UDB's targeting performance using actual administrative data on household eligibility for government social programs, which we compare to auxiliary survey data on their expenditures. We use data from the Indonesian Household Socioeconomic Survey (known as SUSETI), rather than the nationally representative *Susenas*, because the former can be linked to the UDB. In the remainder of this section, we first present the SUSETI data and discuss the procedure for linking households with the UDB. Second, we describe the methods for evaluating targeting accuracy under the pre- and post-UDB regime.

3.1 Indonesian Household Socioeconomic Survey (SUSETI)

The SUSETI sample comprises 5,682 households located in 600 villages spread across six districts where the country's conditional cash transfer program (known by its Indonesian acronym PKH) was to expand in 2011.[11] The survey was originally designed for the purposes of a high-stakes experiment exploring different targeting methods (see Alatas et al., 2013, 2016 for further details). We exploit the fortuitous timing of SUSETI to provide insight into the effectiveness of the UDB. The baseline data were collected in March 2011. A later endline survey was conducted for the targeting experiment in February 2012, but we rely primarily on the baseline round of data because it is more comprehensive in terms of household characteristics, predetermined with respect to PKH benefits rolled out in late 2011, and closer in time to the UDB registration survey conducted in mid-2011.

SUSETI households were randomly selected among those who met the PKH demographic eligibility criteria of having an expectant mother or at least one child under the age of sixteen. This population is important for at least two reasons. First, according to nationally representative household survey data from 2011 (*Susenas*), around two-thirds of Indonesian households have at least one child aged below sixteen. Moreover, these two-thirds of households are more than twice as likely to fall below the poverty line as households with older or no children. These general patterns hold for SUSETI and non-SUSETI

[11] The survey was conducted in three provinces meant to represent a wide range of Indonesia's diverse cultural and economic geography: Lampung (Central Lampung and Bandar Lampung districts), South Sumatra (Ogan Komering Ilir and Palembang districts), and Central Java (Wonogiri and Pemalang districts). The survey initially included 5,998 households, but there is an attrition of about 5% of the original households between the baseline and endline 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 scores (results available upon request). We do not evaluate the PKH program as it had not yet been fully rolled out by the time of our analysis, making it difficult to assess baseline targeting.

districts. Second, in many developing countries and in particular in Indonesia, a number of social safety nets target those same types of households.[12]

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 the identification of households registered in the UDB. We conducted desk-based matching using the names and addresses of household heads and spouses, and the matching results were also verified in the field. Out of the 5,682 households surveyed in the SUSETI, 2,444 or 43 percent are registered in the UDB with an additional 1,048 households on the pre-listing but not ultimately registered in the UDB. This coverage compares favorably to the overall share of these six districts' population registered in the UDB (41 percent). The matching process and its results are described further in Appendix A.

As part of the matching process, we also identify SUSETI households that are on the enumeration pre-listings but not registered in the UDB. This additional subgroup allows us to investigate possible enumeration errors that may occur as a result of the addition and removal of households based on community suggestions. Such *misenumeration* could occur if those added (removed) have on average a higher (lower) socioeconomic status than those that end up being registered in the UDB.

A second important feature of the SUSETI is the availability of information on receipt of the main social protection programs prior to the establishment of the UDB. This allows us to compare the performance of the centralized UDB targeting approach with its more fragmented predecessors. We can then evaluate the change in targeting accuracy for different programs transitioning to using the UDB. At the time of fielding the SUSETI endline in early 2012, the UDB had not yet been used for targeting purposes. However, we know which households were to be included in the beneficiary lists provided to these programs, based on their PMT score rankings in the UDB.

The SUSETI also includes all the indicators used to calculate households' PMT scores in the UDB. This allows us to simulate 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 poor households not being registered in the UDB and those due to limitations of the PMT process.

[12] At the same time, many countries also implement programs targeted at other groups such as the elderly and those with disabilities. In a survey of programs across sub-Saharan African countries, Cirillo and Tebaldi (2016) find that nearly 60 percent of programs target households with children, 32 percent with elderly, and 28 percent with disabilities of some sort (with many cross-cutting programs). Meanwhile, according to Honorati et al. (2015), the number of countries implementing conditional cash transfer programs for schooling and health has more than doubled between 2008 and 2014, from 27 to 64 in 2014, and school feeding programs are among the more common programs in developing countries.

3.2 Methodology for Assessing the Targeting Accuracy of the UDB

Having clarified the potential sources of targeting errors, we now develop the empirical methods for investigating the expected UDB targeting outcomes. A large literature examines different measures and methodologies for estimating targeting accuracy. 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). We use undercoverage and leakage as our main targeting outcomes, in line with most of the literature. Undercoverage, or exclusion error, is defined as the share of households below a given poverty threshold that are not receiving program benefits. For the parametric analysis, we consider two thresholds: (i) *undercoverage* is the fraction of non-recipients below the 30th percentile of household per capita consumption in the SUSETI sample,[13] and (ii) *severe undercoverage* is the fraction below the 10th percentile. These levels correspond closely to the "poor" and "near poor" thresholds used by the Indonesian government to determine eligibility for its main social assistance programs. BLT, and Jamkesmas cover roughly the poorest 30% of households in the country, while the eligibility threshold for PKH is close to the poorest 10%. 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 per capita consumption distribution. The key qualitative insights of our analysis are robust to alternative thresholds, and we use nonparametric regression approach to provide visual evidence of the full distributional incidence.

We assess the targeting performance of the UDB against the baseline targeting performance of Jamkesmas and the BLT. More specifically, we consider the performance expected from the use of lists of eligible beneficiaries from the UDB. Focusing on predetermined 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 program implementation issues that may affect benefit delivery. However, some discrepancy between the expected and actual UDB targeting errors may occur depending on the degree of compliance with the beneficiary lists printed in the capital and provided in the field. This discrepancy should be limited for BLT and Jamkesmas, but we revisit the implications of targeting adherence in our concluding discussion.

We calculate *baseline targeting errors* by comparing reported (pre-UDB) program receipt to household per capita consumption. These estimates reflect the targeting outcomes expected from a "business-as-usual" policy of continuing to allocate social programs to those households deemed eligible through the previous program-specific targeting system. We then calculate the *expected UDB targeting errors* by

[13] In order to render the per capita expenditure (PCE) distribution nationally comparable, we adjust the PCE for households in each district by a factor equal to the ratio of that district's household PCE at the 30th percentile to the household PCE at the 30th percentile in the country's richest district of South Jakarta. The normalization factor is innocuous for our purposes.

comparing, for households registered in the UDB, actual per capita consumption (from SUSETI) with the PMT scores (from the UDB) used to produce beneficiary lists based on each program's eligibility threshold. Any household in the SUSETI sample not found in the UDB through the matching process is considered to be a non-recipient.

The comparison of baseline and expected UDB targeting errors reveals the change in targeting performance due to the transition from program-specific targeting to using a single registry for beneficiary selection. Switching to the UDB implies changes not only in which households will receive program benefits but also in the total number of beneficiaries (i.e., program coverage). Therefore, we first present standard undercoverage and leakage measures to assess the overall change in targeting performance between baseline and with 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 coverage level (i.e., holding constant the number of beneficiaries).

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

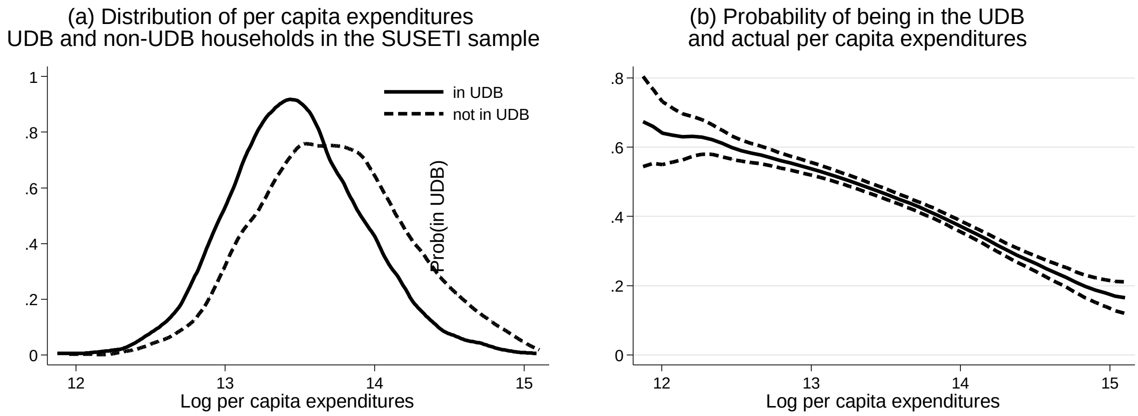
4 Results: UDB Targeting Performance

In this section, we present initial results on the targeting performance of the UDB, taking advantage of the matched SUSETI-UDB-pre-listing data. First, we focus on the registration stage and assess to what extent registered households are poorer than non-registered households, highlighting differences across registration methods. Second, we present the overall UDB performance by comparing program baseline and expected UDB targeting accuracy.

4.1 Are UDB-Registered Households Poorer than Non-Registered Households?

Figure 2 provides an initial glimpse into the UDB's performance in reaching the poorest households. Figure 2(a) shows that UDB households are significantly poorer than non-UDB households. However, there is considerable overlap in the consumption distributions, suggesting that a large share of poor households is not in the UDB. Figure 2(b) 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 more than 60 percent to be in the UDB compared to less than 20 percent for households with the highest consumption levels. This roughly linear figure is far from the "perfect" targeting case, which would look more like a step function with those below the 40th percentile having probabilities close to one and those above having probabilities close to zero. We investigate this gap between actual and perfect targeting in Section 4.2.

Figure 2: Progressivity in the Inclusion of Households in the UDB

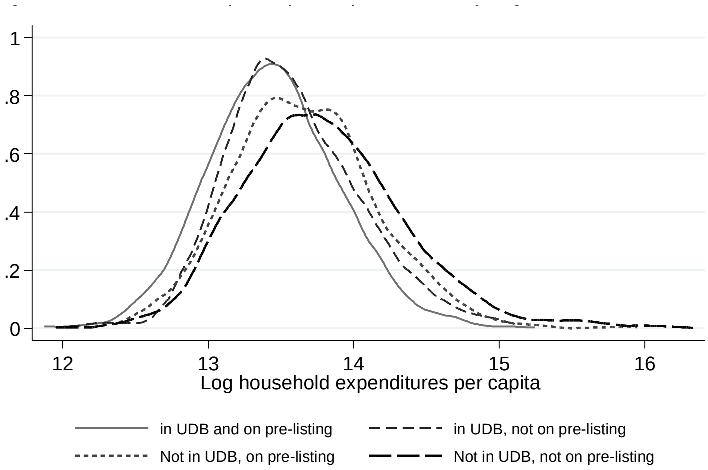


Notes: Figure 2(a) plots the kernel density of log household expenditures per capita separately for SUSETI households registered (not registered) in the UDB. Figure 2(b) plots the kernel regression probability and 90 percent confidence interval of being in the UDB against log expenditures.

Next, we identify which of the different methods used for registering households in the UDB led to more progressive inclusion of the poor. Figure 3 shows that the consumption distribution of UDB households registered based on the pre-listing is shifted to the left (poorer) compared to that of UDB households identified through community suggestions ("in UDB, not on pre-listing"). Both of these distributions are poorer compared to households not registered in the UDB. Households that were removed from the survey enumeration pre-listing, and therefore not registered in the UDB, have a consumption distribution that is similar to other households not registered in the UDB. These distributions suggest that, in the SUSETI sample, UDB households are on average poorer than non-UDB households, regardless of the channel through which they have been registered.[14]

[14] Kolmogorov-Smirnov tests reject equality across all pairwise comparisons of these four distributions.

Figure 3: Distribution of Household Expenditures per Capita, by Registration Channel



Notes: This figure plots the kernel density of log household expenditures per capita for SUSETI households based on their registration channel. Those not on the pre-listing and in the UDB were added through community suggestions after the initial listing.

In Table 1, we provide additional evidence on the socioeconomic differences across households according to their registration channel. Those registered based on the pre-listing have monthly per capita expenditures that are around 15 percent lower on average than those registered through community suggestions. Those registered through the pre-listing also tend to have significantly more family members and children. Their household heads tend to have less schooling and are more likely to be male and working compared to the heads of UDB households registered through community suggestions. Among non-UDB households, those on the pre-listing appear on average poorer, larger, with heads that have two less years of school and are more likely to be male and work. These differences point to the general progressiveness of the pre-listing.

Table 1: Socioeconomic Characteristics of Households in the SUSETI by Registration Channel

	All	**UDB-registered households**		**Non-UDB households**	
		Pre-listing	**Non-pre-listing**	**Pre-listing**	**Non-pre-listing**
Number of Households		2,016	428	1,048	2,190
Per capita expenditures	575,766	459,239	529,064	562,363	698,611
Household size	4.761	5.034	4.334	4.922	4.516
Number of children 0-15 years	1.678	1.854	1.453	1.747	1.528
Age of household head	44.4	44.1	44.6	46.0	43.9
Male household head	0.945	0.957	0.839	0.979	0.939
Household head schooling years	6.889	5.695	6.662	6.440	8.249
Household head works	0.929	0.933	0.864	0.952	0.928
Household head works in agricultural sector	0.448	0.479	0.379	0.552	0.383

Received Jamkesmas health waiver program	0.441	0.604	0.514	0.301	0.342
Received BLT cash transfer	0.395	0.584	0.530	0.267	0.255

Notes: This table reports averages for all households in SUSETI followed by a breakdown for households in the UDB and not in the UDB. Per capita expenditures are nominal *Rupiah* values as reported in the baseline survey. The non-pre-listing households are those registered through community suggestions after the initial listing.

Table 1 also shows that UDB households are more likely than non-UDB households to have previously received social program benefits distributed prior to the implementation of the UDB. For the BLT cash transfer program in 2008, around 55 percent of UDB households report to have been recipients compared to about 25 percent of non-UDB households, and the differences are similar for Jamkesmas. Recall that the SUSETI data was collected before these social programs had begun to use the UDB for selecting beneficiaries. Hence, these baseline figures indicate numbers of previous beneficiaries entering into the UDB and do not show the UDB's anticipated effects on program targeting outcomes, which we explore next.

4.2 Evaluation of Expected UDB Targeting Performance

In this section, we evaluate the changes in targeting accuracy that can be expected from the transition to using the UDB. Column 1 of Table 2 shows that at baseline, 44%, and 39% of all SUSETI households report having previously received Jamkesmas and BLT, respectively. The two programs exhibit similar baseline targeting errors, with leakage rates of 34% and 39%, respectively, and undercoverage rates of 45% and 51%. These targeting error rates for the six districts in SUSETI are in line with previous research analyzing the targeting performance across all of Indonesia (see World Bank, 2012).

Table 2: Baseline and Expected UDB Program Targeting Accuracy

	Baseline (%) (1)	Expected UDB (%) (2)
Panel A: Jamkesmas		
Coverage level	44	33
Leakage	36.9	22.7
Severe Leakage	32.5	17.4
Undercoverage	44.9	52.6
Severe Undercoverage	42.8	48.4
Panel B: BLT		
Coverage level	39	29
Leakage	32.5	19.2
Severe Leakage	27.0	14.5
Undercoverage	50.5	57.6
Severe Undercoverage	48.1	53.7

Notes: This table reports estimates of targeting errors, computed separately for the Jamkesmas and BLT programs. Leakage captures the fraction of the richest 40% of households that received the given program; severe leakage captures the fraction of the richest 20% that received the given program. Severe undercoverage captures the fraction of the poorest 10% that did not receive the given program; undercoverage captures the fraction of the poorest 30% that did not receive the given program. In all columns, households are ranked according to their household expenditures per capita at baseline. The definition of program receipt varies across columns. In column 1, program receipt is as reported by households in SUSETI (before the introduction of the UDB). In column 2, program receipt equals one if the household's PMT score in the UDB places it within the pool of intended program recipients.

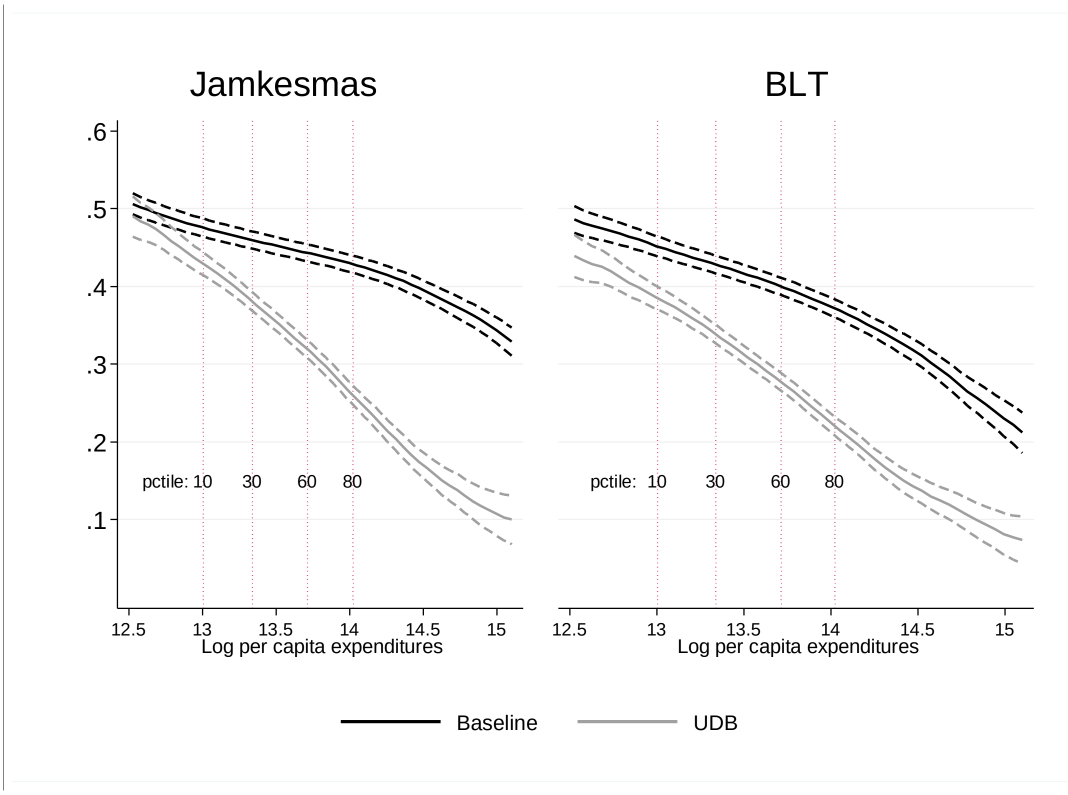
In column 2, we report the expected targeting outcomes based on the use of the UDB beneficiary lists. In calculating targeting performance, program receipt equals one if the household's PMT score falls below the program-specific PMT eligibility threshold.[15] The first finding is that Jamkesmas and BLT coverage levels decrease significantly with the UDB compared to baseline.[16] This reduction in the number of beneficiaries leads to an increase in undercoverage for both Jamkesmas (from 45% to 53%) and BLT (from 51% to 58%). At the same time, the expected decrease in coverage also significantly reduces leakage to non-poor households. BLT baseline leakage of 34% is expected to decrease by 13 percentage points with use of the UDB. For Jamkesmas, baseline leakage rates are expected to fall from 39% to 25%. Similar patterns are observed for the severe measures of undercoverage and leakage, which are lower across all programs.

In Figure 4, we provide a more nonparametric look at the benefit incidence across the two programs. The graphs show kernel regressions of program receipt against log expenditures with 90 percent confidence bands. Importantly, the graphs confirm that the UDB leads to a statistically significant improvement in targeting performance. Under the UDB targeting system, the probability of receiving benefits decreases faster as per capita expenditures increase compared to baseline for both programs despite the decrease in coverage observed for Jamkesmas. Overall, the benefit incidence curves in Figure 4 suggest that targeting using the UDB is more progressive than with the previous approaches to beneficiary selection used in Indonesia.

[15] Nationally, these thresholds are the poorest 30% for Jamkesmas and the poorest 25% for BLT, but within our study areas, the thresholds result in coverage levels of 33% for Jamkesmas and 29% for BLT as seen in the table.

[16] It is possible that these results overstate the extent of exclusion errors on account of misreporting actual program receipt due, for example, to social desirability bias (of saying yes) or confusion about the origin of the health insurance scheme as there are both regional (Jamkesda) and national (Jamkesmas) schemes. Such misreporting works against finding large improvements in undercoverage.

Figure 4: Program Benefit Incidence, Baseline and UDB



Notes: This figure shows the probability of receiving each program at baseline and with the UDB as a function of per capita expenditures, estimated using kernel regressions with an optimal, rule-of-thumb bandwidth and an Epanechnikov kernel. The 90 percent confidence bands are in dashed lines. Baseline program receipt and per capita expenditures are from the SUSETI. UDB program receipt is based on beneficiary lists from the UDB as in Table 2.

The difference between baseline and expected UDB errors is difficult to interpret given the substantial change in program coverage levels taking place concurrently with the transition to the UDB. It is therefore useful to keep coverage levels constant as an alternative way to assess the expected change in targeting performance from transitioning to the UDB. We do this by simulating different alternatives for each program in keeping with the expected changes in scale associated with the transition to the UDB. We compare baseline and expected UDB targeting performance (i) when the baseline coverage level is scaled-down to match the UDB coverage level, with Jamkesmas, and (ii) when the UDB coverage level is scaled-up to match the baseline coverage level, with BLT. Specifically, in column 1, panel A of Table 3, we use the share of households that reported receiving the program at baseline in SUSETI in each decile to reconstruct Jamkesmas baseline program receipt at UDB coverage level. For example, with a coverage of 44% of the population at baseline, we find that 57% of households in the first decile receive Jamkesmas. We then randomly assign program receipt to 43% (i.e., 57% times the ratio of simulated and actual coverages) of households in the first decile to simulate a scaled-down Jamkesmas program covering 33% of the population. In column 2, Panel B of Table 3, we reconstruct BLT program receipt with the UDB by assigning receipt to all UDB households with PMT scores ranked below the number of households reporting to receive BLT at baseline in each district. For example, if there are 100 out of 300 households receiving BLT in district A at baseline, we assign simulated program receipt to the 100 UDB households with the lowest PMT. This approach ensures that the results we obtain in terms of targeting effectiveness are not due to a substitution of households across districts.

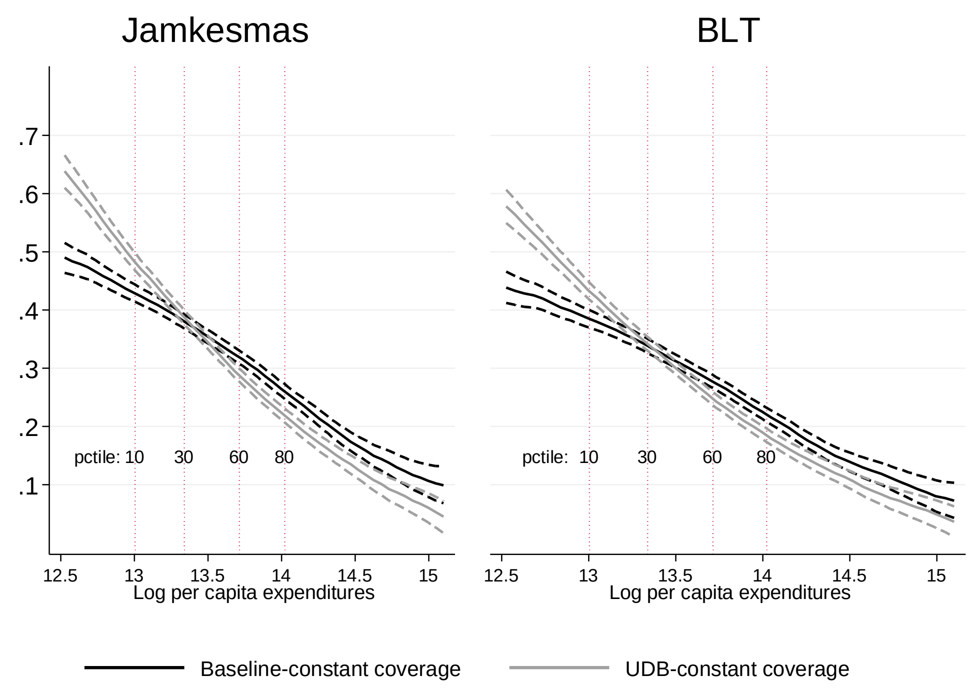
Table 3: Comparing Baseline and UDB Targeting Accuracy at the Same Coverage Levels

	Baseline (%) (1)	UDB (%) (2)
Panel A: Jamkesmas - actual UDB coverage levels and baseline beneficiary selection		
Coverage level	33	33
Leakage	27.6	22.7
Severe Leakage	24.2	17.4
Undercoverage	58.8	52.6
Severe Undercoverage	57.2	48.4
Panel B: BLT - actual baseline coverage levels and UDB-based beneficiary selection		
Coverage level	39	39
Leakage	32.5	28.8
Severe Leakage	27	24
Undercoverage	50.5	47.7
Severe Undercoverage	48.1	44.2

Notes: This table reports estimates of targeting errors at the same coverage levels, defined and computed separately for the Jamkesmas and BLT programs. See the notes to Table 2 for definitions of the different targeting performance measures. In all columns, households are ranked according to their household expenditures per capita at baseline. The definition of program receipt varies across programs and columns. Jamkesmas: In column 1, program receipt is reconstructed for each decile using the share of households that reported to receive the program at baseline in SUSETI in each decile, applied to the number of households deemed eligible for the program based on the UDB. In column 2, program receipt equals one if the household's PMT score falls below the program-specific eligibility threshold. BLT: In column 1, program receipt is as reported by households in SUSETI. In column 2, the BLT program receipt is based on ranking the household PMT scores and taking all households with PMT scores up to the number of households reporting BLT receipt in SUSETI.

Table 3 shows that holding coverage levels constant, using the UDB to select beneficiaries leads to a meaningful decrease in both undercoverage and leakage compared to baseline targeting mechanisms. For the Jamkesmas program, using baseline targeting mechanisms for the same number of beneficiaries predicted to be eligible by the UDB would increase leakage from 23% to 28%, and severe leakage from 17% to 24%, as shown by comparing Tables 2 and 3. For the BLT program, using the UDB at constant baseline coverage levels would reduce undercoverage from 51% to 48% and leakage from 32% to 29%. Figure 5 provides the semiparametric benefit incidence curves for the two columns, analogous to the previous figure.

Figure 5: Program Benefit Incidence, Baseline and UDB at the Same Coverage Levels



Notes: This figure shows the probability of receiving each program at baseline and with the UDB as a function of per capita expenditures, estimated using kernel regressions with an optimal, rule-of-thumb bandwidth and an Epanechnikov kernel. The 90 percent confidence bands are in dashed lines. Baseline program receipt and per capita expenditures are from the SUSETI. Baseline and UDB are based on the formulations in Table 3.

The reduction in exclusion errors under this constant coverage counterfactual further suggests that the main reason for the increase in undercoverage noted earlier in this section is the concurrent decrease in coverage levels, compared to baseline. Extrapolating, this improvement in targeting implies over 12,000 additional households from the poorest 30 percent with at least one child under the age of sixteen receiving this program in our study districts.

To summarize, holding coverage levels constant, the UDB is predicted to improve both undercoverage and leakage relative to baseline. Although the percent gains seem modest, the returns to improved coverage of the poorest members of society are potentially quite significant.

5 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 ranking stage. In this section, we attempt to disentangle these two sources of targeting errors in order to highlight distinct policy implications. We focus first on errors resulting from the enumeration process using ‘reconstructed’ PMT scores calculated for all households in the SUSETI sample, instead of focusing only on those matched households who are actually registered in the current UDB. We then assess errors resulting from the ranking process and investigate a simple improvement to the approach used to rank households actually registered in the UDB.

5.1 Misenumeration Errors

Improving the enumeration process by increasing the number of households registered in the UDB is one of the possible options to improve the targeting performance of the single registry. Here, we assess the performance of the UDB 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). By simulating outcomes under this census-based scenario, we remove potential errors due to poor households not being enumerated and instead isolate the role of the PMT-based ranking process in contributing to targeting errors.

We reconstruct PMT scores for all households in the SUSETI sample by applying the original district-specific PMT algorithms used by UDB planners to the same variables collected for each household in SUSETI. We then calculate targeting errors by comparing household expenditure rankings from SUSETI against program eligibility status (based on the reconstructed PMT scores and UDB-based coverage levels as in column 2 of Table 2).

Table 4 shows the improvement in targeting errors expected under this full census scenario relative to the UDB targeting errors presented earlier. Leakage and undercoverage rates in the UDB are projected to improve under this scenario for both Jamkesmas and BLT, by about 18% and 11-14%, respectively. The improvements are even more striking for severe leakage and particularly for severe undercoverage, with gains in the latter ranging from 25-31% across programs. In other words, expanding the number of households enumerated in the national targeting survey holds significant potential to improve targeting outcomes, particularly by reducing exclusion of the poorest.

Table 4: Expected Change in Targeting Accuracy with Full Census Enumeration

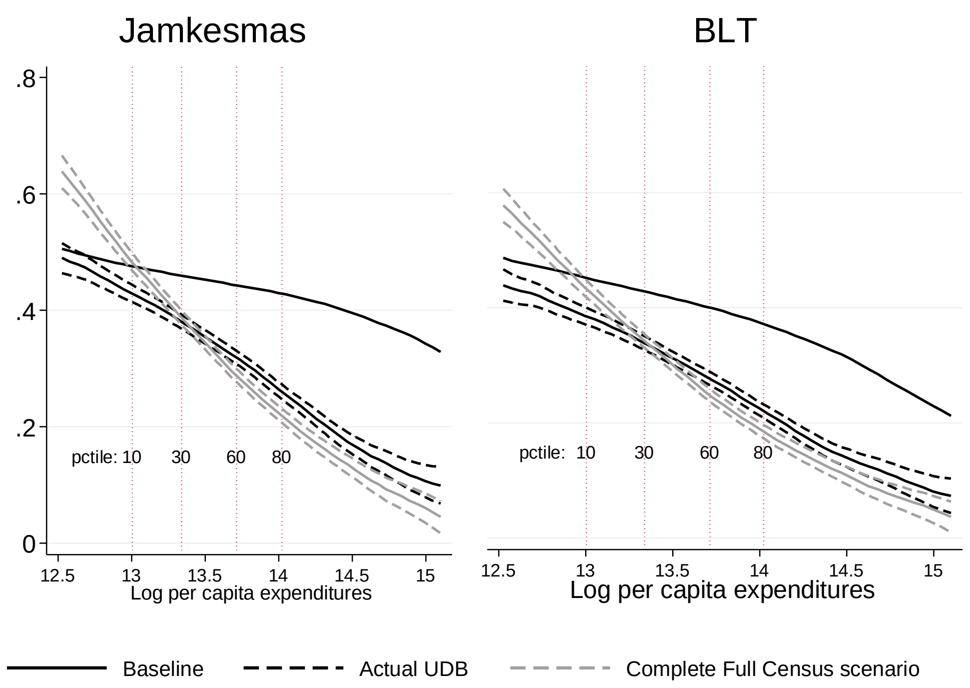
	Expected UDB (%)	**Full census enumeration (%)**	**Change in targeting errors: census compared to UDB (%)**
	(1)	(2)	(3)
Panel A: Jamkesmas			
Leakage	22.7	18.7	-17.6
Severe Leakage	17.4	14.2	-18.4
Undercoverage	52.6	45.2	-14.1
Severe Undercoverage	48.4	33.5	-30.8
Panel B: BLT			
Leakage	19.2	15.8	-17.7

Severe Leakage	14.5	12.1	-16.6
Undercoverage	57.6	51.1	-11.3
Severe Undercoverage	53.7	40.5	-24.6

Notes: This table reports estimates of UDB targeting errors based on the PMT scores of households actually registered in the UDB (column 1), and on reconstructed PMT scores (from SUSETI variables) for all SUSETI households, i.e. simulating a scenario of full census enumeration (column 2). For column (2), program receipt equals one for all households with reconstructed PMT score rankings that fall below the number of households in SUSETI that are eligible for program receipt based on the UDB. Change (column 3) is calculated as a share of expected UDB errors. A negative sign indicates a decrease in targeting errors under the full enumeration scenario compared to actual UDB. See the notes to Table 2 for definitions of the different targeting performance measures.

Figure 6 provides a nonparametric look at benefit incidence based on this full enumeration scenario compared to the baseline and UDB-targeted receipt as presented in Figure 4. In line with results from Table 4, households from the poorest two to three consumption deciles have a significantly higher probability of receiving program benefits when considering PMT-specific predictions for all SUSETI households, as opposed to UDB households only. This census scenario also leads to a slight reduction in leakage, as shown by the lower program receipt probability for households in the upper portion of the consumption distribution. Some of these improvements in targeting are of course a mechanical result due to the expanded inclusion of poorer households in the registry.

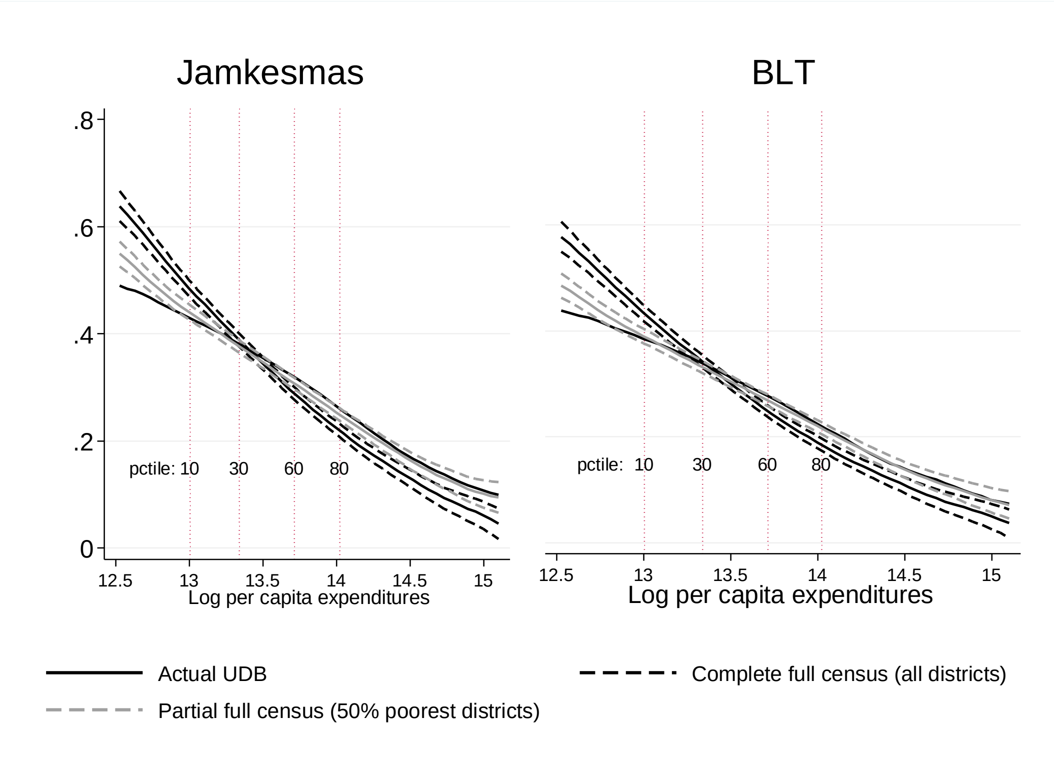
Figure 6: Program Benefit Incidence in Baseline, UDB and Full Census Scenarios



Notes: Baseline program receipt and per capita expenditures are from the SUSETI. "Actual UDB" refers to SUSETI households matched with the UDB and ranked using their PMT score from the UDB. "Full Census scenario" 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. All curves are based on kernel regressions with a rule-of-thumb bandwidth and an Epanechnikov kernel. The dashed lines are 90 confidence bands. The bottom percentile is trimmed for presentation purposes, but results are similar when it is included.

In Figure 7, we analyze an alternative scenario in which we conduct a full enumeration in the poorest half of districts of the sample and a UDB-based registration in the richest half. This less costly, quasi-geographic targeting approach also yields some improvements in both undercoverage and leakage when compared to program incidence with actual UDB-targeted receipt. However, as expected, improvements in undercoverage under this middle scenario are slightly lower than with full census enumeration in all districts. For the Jamkesmas program, for example, the poorest households have a probability of about 65 percent of receiving the program under a complete full enumeration scenario. Under a scenario with full enumeration only in the poorest half of districts, this probability is about 10 percentage points lower. Furthermore, compared to the actual UDB, there is no significant change in leakage for both Jamkesmas and BLT under the partial census approach. Together, the results in Figures 6 and 7 point to the significant improvements in coverage among the poorest ten percent of households when moving to the full enumeration approach.

Figure 7: Program Benefit Incidence, Actual UDB vs. Complete and Partial Full Census Scenarios



Notes: "Actual UDB" refers to SUSETI households matched with the UDB and ranked using their PMT score from the UDB. "Complete full census" refers to all households in the SUSETI sample ranked according to their PMT score reconstructed using the underlying PMT variables from SUSETI. "Partial full census in 50% poorest districts" refers to all households in the SUSETI sample ranked according to their PMT score reconstructed using the underlying PMT variables from SUSETI in the three poorest districts of the sample and to households matched with the UDB in the three richest districts. All curves are based on kernel regressions with a rule-of-thumb bandwidth and an Epanechnikov kernel. The dashed lines are 90 percent confidence bands. The bottom percentile is trimmed for presentation purposes, but results are similar when it is included.

Nevertheless, we acknowledge that even under full enumeration, undercoverage appears high. This persistent targeting error points to two important limitations of any analysis relying on a static measure of expenditures as the main indicator of welfare. First, in a context where expenditures churn quite often, we may erroneously identify a household as more or less "eligible" for a given program when, in fact, their actual beneficiary status reflects superior local knowledge about dynamic welfare status.[17] Although this is an inherent shortcoming of studies constrained to use static targeting metrics, such high rates of churning make it difficult to develop a scheme that fully eliminates targeting errors.

Second, and perhaps more fundamental, expenditure-based approaches to targeting may not adequately capture welfare, particularly in a setting where there is not uniform agreement as to the mapping between material well-being and welfare. At the same time, local community members may be able to more effectively discriminate between poor and non-poor based on broader notions of welfare not captured by expenditures alone. This idea is nicely illustrated in a series of studies in the Indian village of Palanpur (Bliss and Stern, 1982; Lanjouw and Stern, 1991, 1998)[18] and is also borne out in an experimental study on targeting within Indonesian villages (Alatas et al, 2012). While such evidence does not mean that policymakers should abandon expenditure-based targeting, it does argue for continuing to explore ways to incorporate other dimensions of poverty as well as feedback from community members.[19]

5.2 Misclassification Errors

As described earlier, the UDB registration survey collected basic individual- and household-level information that was used in the ranking stage to estimate socioeconomic status following a PMT approach. However, several indicators were not included in the UDB registration survey due to time and financial constraints. In addition, when estimating PMT scores, it is common to avoid using indicators that are difficult to observe directly by enumerators and therefore prone to misreporting by respondents attempting to increase their chance of receiving program benefits.[20] These "partially hidden assets" can be easily misreported during a survey but are often commonly verifiable within the community.

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[17] Churning around the poverty line is pervasive across Indonesia. Although the poverty rate is just above 10 percent nationally, the operating definition of "poor and vulnerable" households extend up to the 40th percentile, which is supported by longitudinal evidence on churning. Using *Susenas* panel data from 2008-2010, we find that around 45 percent of households that are poor in 2010 were also poor in 2008 while around 50 percent of the poor in 2009 are not poor in 2010.

[18] Lanjouw and Stern (1991), for example, discuss the case of an ascetic who owns many assets but spends very little out of choice rather than constraints, something apparent to community members but perhaps not to outside observers.

[19] In fact, the targeting criteria used in the past in Indonesia included measures of well-being not typically available in household survey inputs to PMTs. Implemented by the National Family Planning Coordination Board, these criteria included, for example, questions on whether all members of the family were able to freely worship according to their religion and whether family members were able to participate in community social activities. These non-material measures of wellbeing are potentially important and yet largely excluded from most PMT-based targeting surveys today.

[20] This is a higher risk when respondents are aware that the survey is being conducted for the purpose of selecting beneficiaries of social assistance programs. In Colombia, Camacho and Conover (2011) provide evidence that when the PMT formula becomes known there is an increase in misreporting to increase one's chances of receiving program benefits.

In this section, we assess the performance of the UDB that would be observed if the PMT-based ranking process utilized additional information on household ownership of partially hidden assets. Taking advantage of this additional information available in the SUSETI, we construct "negative lists" including households that have been registered in the UDB but that own partially hidden assets. By simulating outcomes under this negative list scenario, we are able to evaluate the potential impact of a simple improvement to the ranking process in contributing to targeting accuracy while holding the enumerated population constant.

We consider four types of hidden assets: (1) savings above IDR 500,000 (about USD 40); (2) savings and/or gold above IDR 500,000; (3) livestock valued above IDR 500,000; and (4) landholdings larger than 0.2 hectares.[21] Under this simulation exercise, households that own partially hidden assets are de facto ineligible, even if they are registered in the UDB. For each program, we designate as eligible those households that are registered in the UDB and do not own such assets. We then calculate targeting errors by comparing actual household expenditure rankings against this new program eligibility status (based on actual UDB PMT scores, the negative list, and on UDB-based coverage levels, see column 2 of Table 3).

Table 5 shows the improvement in targeting errors expected under a negative list scenario based on ownership of savings of a value higher than USD 40, relative to UDB targeting errors presented in Section 4.2. Results based on ownership of the other assets are similar and are presented in Appendix B. The use of additional information to assess household eligibility generates little improvement in both leakage and undercoverage rates. For the Jamkesmas program for example, the negative list would generate small improvements in leakage, by 3-5 percent, and in undercoverage, by 2-5 percent. This could be related to the fact that the UDB already performs quite well in filtering rich households in the early registration stage with local community input. As a result, applying an additional layer of screening at the ranking stage holds limited potential to significantly improve targeting accuracy.

Table 5: Expected Change in Targeting Accuracy When Augmenting PMT Classification with Negative Lists

	Expected UDB	**PMT + Neg. List 1**	**Change in targeting errors: Neg. List compared to UDB (%)**
	(1)	(2)	(3)
Panel A: Jamkesmas			
Coverage (No. Households)	1858	1858	
Leakage	22.7	21.9	-3.5
Severe Leakage	17.4	16.6	-4.6
Undercoverage	52.6	51.5	-2.1
Severe Undercoverage	48.4	46.1	-4.8

[21] Descriptive statistics about these difficult-to-verify assets are presented in Appendix B.

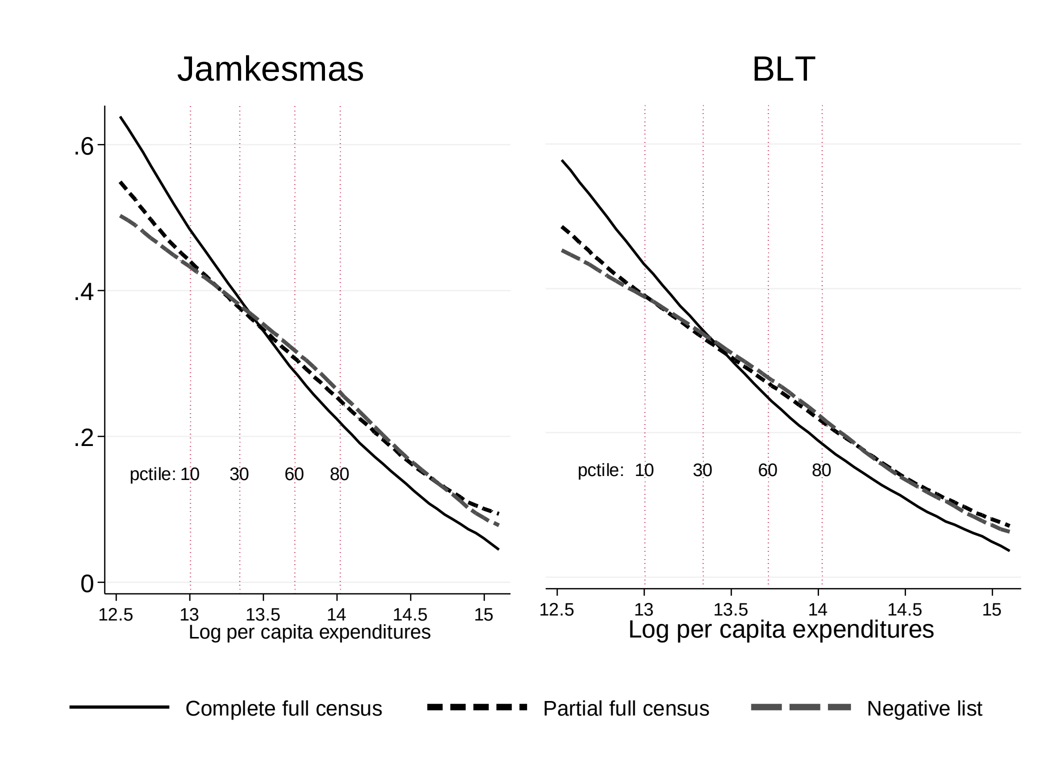
Panel B: BLT			
Coverage (No. Households)	1628	1628	
Leakage	19.2	18.5	-3.6
Severe Leakage	14.5	13.8	-4.8
Undercoverage	57.6	56.6	-1.7
Severe Undercoverage	53.7	51.9	-3.4

Notes: This table reports estimates of UDB targeting errors based on the PMT scores of households actually registered in the UDB. Column 1 reports errors based on actual beneficiary lists issued from the UDB. Column 2 reports targeting errors in simulated negative list scenarios. Program eligibility is determined using actual PMT scores and ownership of savings above IDR 500,000. The change in Column 3 is calculated as a share of expected UDB errors from Table 2. A negative (positive) sign indicates a decrease (increase) in targeting errors under the negative list scenario based on ownership on savings compared to actual UDB. See the notes to Table 2 for definitions of the different targeting performance measures.

Compared to the alternative enumeration schemes in Section 5.1, the addition of criteria used to assess the eligibility of households registered in the UDB has relatively limited potential to improve targeting outcomes. In Figure 8, we further compare the improvements in targeting associated with partial or full enumeration versus the negative listing approach. Across programs, we find little difference between the partial full enumeration and negative listing approaches while the full enumeration approach retains its advantages, particularly among the poorest. These reductions in severe undercoverage with full enumeration are evident in the lower tail of the expenditure distribution in Figure 7 and even more clearly in Appendix Figure C.1.[22] Indeed, these gains in coverage for the very poor are a key feature of the full enumeration approach, which ensures that all households are given equal opportunity to be considered under the eventual PMT approach. With the inclusion of all households in the PMT modeling comes greater progressivity in overall targeting as the incidence of exclusion falls less and less on poorer households.

[22] Appendix Figure C.1 nonparametrically estimates the exclusion probabilities in the bottom three deciles for the two programs across UDB, full enumeration, and negative listing targeting schemes. While baseline exclusion errors are relatively uniform across the expenditure distribution in the bottom three deciles, the full enumeration approach covers significantly more households in the bottom decile

Figure 8: Program Benefit Incidence, Full Census vs. Negative List scenarios



Notes: Per capita expenditures are from the SUSETI. "Complete full census" refers to all households in the SUSETI sample ranked according to their PMT score reconstructed using the underlying PMT variables from SUSETI. "Partial full census" refers to all households in the SUSETI sample ranked according to their PMT score reconstructed using the underlying PMT variables from SUSETI in the three poorest districts of the sample and to households matched with the UDB in the three richest districts. "Negative list" refers to SUSETI households matched with the UDB which do not own any of the hidden assets considered and ranked using their PMT score from the UDB. All curves are based on kernel regressions with a rule-of-thumb bandwidth and an Epanechnikov kernel. The bottom percentile is trimmed for presentation purposes, but results are similar when it is included. Confidence bands are omitted for presentational purposes but fully overlap for the partial full census and negative listing approaches.

5.3 Cost Effectiveness

Having documented the potential benefits of full enumeration, we argue here that the large-scale data collection effort required to achieve these benefits can be cost effective. Given the caveats already mentioned, we extrapolate these findings to the full population (with at least one child aged below sixteen) in our study districts. The proposed full enumeration scenario would imply increasing the number of such households surveyed from around 470,000 to 1.1 million. Among the additional households that would be registered under this scenario, around 210,000 can be assumed to be in the poorest 30 percent.

Put differently, our full enumeration estimates imply that households from the poorest three deciles would be more likely to receive Jamkesmas by about 7 percentage points, and more likely to receive BLT by about 8 percentage points. Benefit levels of Jamkesmas and BLT amount annually to a total of

IDR 1.16 million (about USD 90) per household or IDR 960,000 and 200,000, respectively.[23] We assume that the unit cost of surveying the remaining population of these districts would be similar to the one incurred in establishing the UDB— IDR 25,000 (USD 2) per household for a survey being used over a three-year period.[24] It then follows that surveying the full population would cost about 11 percent of the value of additional benefits that would be received annually by households with at least one child aged below sixteen from the poorest three deciles in SUSETI districts.

Overall, these results point to the feasibility of achieving substantial targeting improvements with additional surveying input. We acknowledge, though, that the implied cost-benefit ratio may differ in other low-income countries (and) with less well-developed statistical enumeration capacity.

6 Discussion

This paper evaluates the effectiveness of one of the world's largest targeting systems for delivering social program benefits. We show that the use of the Unified Targeting Database (UDB) in Indonesia is expected to significantly reduce leakage of benefits to non-poor households. However, undercoverage remains relatively high and is due largely to the difficulties of enumerating the right households for inclusion in the UDB. We predict a significant decrease in undercoverage under simulations that consider enumerating a larger set of households before proceeding to the stage of estimating PMT scores. By relying on a unique combination of administrative and survey data, we are able to provide the first evidence on the relative importance of enumeration versus PMT errors in determining the overall effectiveness of a large-scale targeting system. Our findings suggest practical strategies for improving the effectiveness of national targeting registries recently established across the developing world.

Our key results highlight the value of increasing 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. While it is commonly argued that it is too expensive to visit the entire population, we find that, under a reasonable set of assumptions, the costs of surveying the remaining population from our study districts amounts to only 11 percent of the value of additional benefits received by households from the poorest three deciles previously omitted from the registry. If conducting a full census is nevertheless cost-prohibitive, a related option would be first to identify the poorest areas based on poverty maps at higher levels of geographic aggregation where they tend to be more reliable, and then to survey all households in these geographic areas. We provide evidence

[23] For Jamkesmas, we take 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 percent, which amounts to about IDR 80,000 per month for a household of four members. For BLT, we take the value of benefits provided in 2013—IDR 600,000 per household per year—and divide it by three, assuming that this temporary compensation program is only implemented once during a three-year period. In the past, BLT provided households with IDR 1.2 million (2005) and IDR 900,000 (2008).

[24] Based on the 2010 Population Census and 2011 Susenas, there are a total of about 1.6 million households in our study districts, among which 1.15 million have at least one child aged below 16.

suggesting the targeting gains from this approach would also be relatively larger than those from improving the PMT estimates by adding more difficult to observe assets.

Although beyond the implications of our study, another complementary strategy deserving of future investigation would be to transform the household targeting system registration into a more open process in order to allow greater entry. Other developing countries, like 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 program are allowed to apply for inclusion in the registry. This approach may contribute to improve the performance of registries in terms of undercoverage in a situation where there is substantial churning in and out of poverty by allowing households to apply when their circumstances change.[25] In a randomized pilot experiment in Indonesia, Alatas et al. (2016) find that self-targeting leads to similar undercoverage as full enumeration at a lower overall cost, since it surveys fewer households. However, further research is needed to assess the cost-effectiveness of these different strategies, especially given evidence that self-targeting excludes some of the poorest households (that do not apply) and leads to higher costs directly incurred by poor households.

Either of these strategies could be further bolstered with 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) shows that going from 10 to 30 indicators included in a PMT formula does not significantly increase the accuracy of predicted household poverty levels; nor does it reduce targeting errors.[26]

Finally, 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 program benefits. A growing literature examining the political economy of targeting shows that in practice, official beneficiary lists may be modified in the field, which may positively or negatively affect targeting outcomes. Such targeting rule violations may prove beneficial if they allow the community to exercise their greater ability to identify the very poor (Alatas et al., 2012), or if the capture of program benefits by local elites is limited or generates relatively small welfare

[25] In addition, in order to take advantage of local knowledge about households' welfare, an on-demand application system should be combined with local appeal committees comprising community members. These appeal committees could in particular reassess the eligibility status of households that feel they have been wrongly excluded from certain programs, 'out of the PMT box'.

[26] Dreze and Khera (2010) go even further by proposing to use simplified targeting criteria so that "every household can attribute its inclusion in, or exclusion from, the list to a single criterion". Results from Niehaus et al. (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.

losses (Alatas et al., 2013). In Indonesia, past research suggests some departures from intended policy, but overall adherence to official beneficiary lists has typically been quite high (World Bank, 2012). In contrast, in the case of India's Below-Poverty Line (BPL) cards, Niehaus et al. (2013) provide evidence that targeting rule violations by local officials are due to corrupt behavior, which renders BPL's *de facto* allocation much less progressive than the *de jure* allocation. 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.

We conclude with an important note about generalizability. Although our results depend on the specific spatial distribution of poverty, the key features of poverty across Indonesia—limited geographic concentration as well as a relatively high degree of within-village inequality even in poor areas[27]—are not unlike those found in other developing countries (see, for example, Elbers et al., 2004; 2007). The success of any particular combination of geographic and individual targeting will hinge on the particular spatial distribution. For countries with more extreme spatial concentration of poverty than Indonesia, it is plausible that the benefits of geographic targeting will be relatively higher, thereby making a case for alternatives to the purely individual-level targeting being promoted through the expansion in national targeting registries. However, it is also possible that in countries with less within-locality inequality, the exclusion errors arising from full-enumeration strategy will be much more limited.

Nevertheless, we acknowledge the possibility that the reduction in leakage when moving to a national targeting registry (based on full enumeration) may be disproportionately larger than the reduction in undercoverage. Ultimately, this reduction in leakage has important implications for the political economy of support for redistribution that should be reconciled with the persistent exclusion of some subset of poor households from such schemes.

Overall, though, our evaluation should provide new evidence to ongoing debates about the relative merits of different types of registry-based targeting schemes. Understanding how and why these schemes may vary in their effectiveness across countries is an important task for future research.

[27] For example, using the July 2010 *Susenas* data, we find that around 85 percent of the variation in household expenditures lies within districts (the nearly 500 administrative units at which the survey is representative). Within-district inequality dominates at similar levels when looking at indicators for households falling below the 10th or 30th percentiles nationally, which are our cutoffs for defining, respectively, severe undercoverage and undercoverage in targeting. The variation in household poverty status (defined by district-specific poverty lines) is even starker with 96 percent of the variation in poverty status being within-district and only 4 percent between districts. This provides one reason why pure geographic targeting is likely to be ineffective in Indonesia.

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Supplementary Online Appendix

Appendix A: Matching SUSETI with UDB Administrative Data

Before the SUSETI endline 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 that were not registered in the UDB. During the endline survey fielding, enumerators and community leaders were asked to verify that the electronic matches were correctly identified. They were also asked to identify any other matches not yet identified by comparing the SUSETI listing with the UDB registry. The field-based verification process makes "false positive" matches very unlikely, but a small number of "false negative" matches may exist (i.e., SUSETI households who are also in the UDB but the match was not detected), due to the difficulty in recognizing different versions of names. The expected effects of such potential under-matching would be to slightly inflate the estimated errors of exclusion and to slightly deflate estimated errors of inclusion.

Table A.1: Results of Dataset Matching: Share of UDB households in the total population and in the SUSETI

	Total Population			**SUSETI Sample**		
District	UDB	All	Share in UDB (%)	UDB	All	Share in UDB (%)
Central Lampung	58,576	132,554	44	739	1,408	52
Bandar Lampung	81,003	223,730	36	215	459	47
Ogan Komering Ilir	82,110	226,705	36	344	1,056	33
Palembang	53,693	149,010	36	380	826	46
Wonogiri	50,040	138,369	36	276	984	28
Pemalang	121,031	211,100	57	490	949	52
All	**446,453**	**1,081,468**	**41**	**2,444**	**5,682**	**43**

Notes: This table shows the percent of PKH-eligible households, i.e. households with children aged below 16, 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 below 16 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').

Table A.1 shows the results of the matching process used to determine which households from the SUSETI survey are registered in the UDB. Overall, 41 percent of the PKH eligible population in the SUSETI districts is registered in the UDB. Given regional variation in rates of poverty and vulnerability, the matching percentage differs across districts, from 28 percent of the SUSETI sample in Wonogiri to 52 percent in Central Lampung and Pemalang.[28]

[28] 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 there may be local-level characteristics that affect the matching rate. However, we obtain similar results to Table B.1 when considering district-specific average village shares of UDB households in the population and in the SUSETI sample.

Appendix B: Incorporating Partially Hidden Assets in the PMT

Table B.1: Household Hidden Assets

	Observations		Mean		
Negative Lists	UDB	non-UDB	UDB	non-UDB	t-stat
1: Private savings ≥ IDR 500,000	227	913	0.09	0.28	18.12
2: Gold and/or private savings ≥ IDR 500,000	466	1372	0.19	0.42	19.18
3: Livestock valued at IDR 500,000 or more	412	853	0.17	0.26	8.56
4: Farm land > 0.2 ha	432	921	0.18	0.28	9.51

Notes: Negative lists 1 to 3 are based on ownership of savings, gold and livestock of a value higher than 500,000 (USD 40); negative list 4 is based on ownership of farm land of a size larger than 0.2 ha.

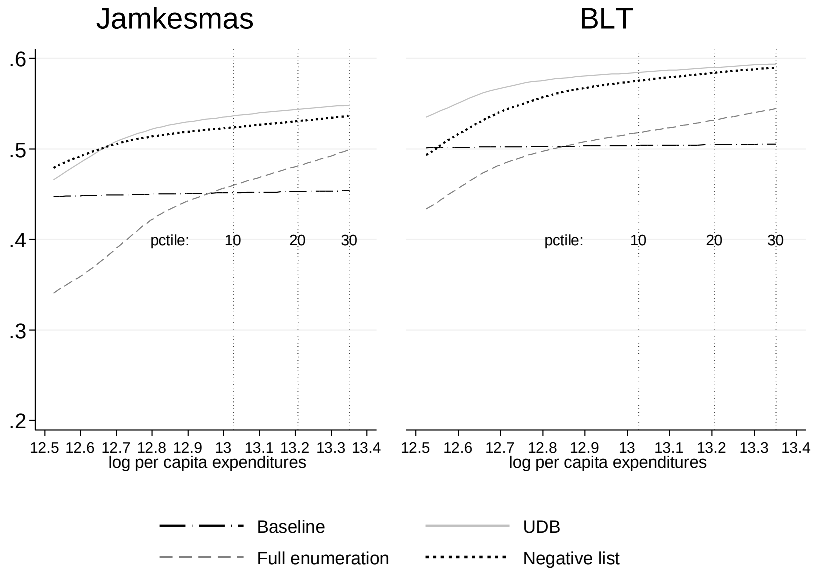
Table B.2: Expected Change in Targeting Accuracy When Augmenting PMT Classification with Negative Listss

	Expected UDB	**PMT + Neg. List 1**	**Change in targeting errors – Neg. List 1 compared to UDB (%)**	**PMT + Neg. List 2**	**Change in targeting errors – Neg. List 2 compared to UDB (%)**	**PMT + Neg. List 3**	**Change in targeting errors – Neg. List 3 compared to UDB (%)**	**PMT + Neg. List 4**	**Change in targeting errors – Neg. List 4 compared to UDB (%)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Jamkesmas									
Coverage (No. Households)	1858	1858		1820		1694		1776	
Leakage	22.7	21.9	-3.5	21	-7.5	20.5	-9.7	21.2	-6.6
Severe Leakage	17.4	16.6	-4.6	16.4	-5.7	16.1	-7.5	16.2	-6.9
Undercoverage	52.6	51.5	-2.1	51.6	-1.9	56.2	6.8	54.6	3.8
Severe Undercoverage	48.4	46.1	-4.8	45.4	-6.2	51.1	5.6	49.3	1.9
Panel B: BLT									
Coverage (No. Households)	1628	1628		1624		1515		1593	
Leakage	19.2	18.5	-3.6	18.4	-4.2	17.7	-7.8	18.6	-3.1
Severe Leakage	14.5	13.8	-4.8	13.8	-4.8	13.5	-6.9	14	-3.4
Undercoverage	57.6	56.6	-1.7	56.2	-2.4	60	4.2	58.1	0.9
Severe Undercoverage	53.7	51.9	-3.4	49.8	-7.3	54.8	2.0	52.8	-1.7

Notes: This table reports estimates of UDB targeting errors based on the PMT scores of households actually registered in the UDB. Column (1) reports errors based on actual beneficiary lists issued from the UDB. Columns (2), (4), (6) and (8) report targeting errors in simulated negative list scenarios. Program eligibility is determined using actual PMT scores and ownership of savings (col. 2); savings and/or gold (col. 4); livestock (col. 6); and farm land (col. 8). BLT eligiblity is based on the same procedure as in Table 4, i.e. on ranking households registered in the UDB by their PMT scores and taking all households with PMT scores up to the number of households reporting BLT 2008 receipt in SUSETI. Changes in columns 3, 5, 7 and 9 are calculated as a share of expected UDB errors from Table 3 (Table 4 for BLT 2008). A negative (positive) sign indicates a decrease (increase) in targeting errors under the negative list scenario based on ownership on savings compared to actual UDB.

Appendix C: Additional Results

Figure C.1: Exclusion Errors among the Poor across Different Targeting Schemes



Notes: This figure assesses targeting errors across the poorest three deciles. Per capita expenditures are from the SUSETI. "Baseline" shows the relatively uniform exclusion errors across the bottom three deciles. "UDB" shows the expected targeting outcomes under the UDB. "Full enumeration" refers to all households in the SUSETI sample ranked according to their PMT score reconstructed using the underlying PMT variables from SUSETI. "Negative list" refers to SUSETI households matched with the UDB which do not own any of the hidden assets considered and ranked using their PMT score from the UDB. All curves are based on kernel regressions with a rule-of-thumb bandwidth and an Epanechnikov kernel. The bottom percentile is trimmed for presentation purposes, but results are similar when it is included. Confidence bands are omitted for presentational purposes but fully overlap for the partial full census and negative listing approaches.