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TARGETING
POOR AND VULNERABLE HOUSEHOLDS IN INDONESIA

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Foreword

Indonesia has experienced strong economic growth over the last forty years. At the same time, the proportion of Indonesians living below the poverty line has fallen dramatically. Nonetheless, around 12 percent of Indonesians remain in poverty and another 30 percent remain highly vulnerable to falling into poverty in any given year. In addition, Indonesia has experienced a number of crises in the last two decades, and such shocks are likely to continue in the future in an increasingly integrated global economy.

Over the last fifteen years the Government has been developing social assistance programs designed to promote the poor out of poverty and protect poor and vulnerable households from both individual and more widespread shocks. The coverage, design and implementation of these programs continues to be improved as social protection in Indonesia matures, but a number of issues remain. One of the most important, and difficult, is how these programs can accurately target households who need them most.

The challenge is to develop a targeting approach which includes most of the poor and vulnerable while minimizing leakage to the rich. At the same time, the system must be feasible, affordable, and accepted and used by all. Furthermore, identifying which households are poor is a difficult task in any developing country, but is particularly so in Indonesia, which has a very large population, a high degree of geographic dispersion, decentralization of much budgetary and operational governance, and frequent entry and exit of households into and from poverty.

Targeting Poor and Vulnerable Households in Indonesia provides the first comprehensive review of targeting for social assistance programs in Indonesia. This evidence-based report builds in part on innovative research done collaboratively with the Government of Indonesia. In this respect Indonesia is contributing to the frontier of global knowledge on targeting, while also drawing on the experience of other countries.

Moving from a thorough assessment of the current effectiveness of targeting in Indonesia, the report contains practical and detailed recommendations for the future. In particular, a National Targeting System is proposed, which envisages developing a single registry of potential beneficiaries to target social assistance to the right households, resulting in more accurate and cost-effective targeting outcomes, and ultimately stronger program impacts.

It is our sincere hope that this report will contribute to the ongoing improvements being made to Indonesia's social assistance programs. As these reforms continue, more Indonesian households will make their way out of poverty, and many more can be protected from the reoccurring shocks making them vulnerable to falling back into poverty.

Stefan Koeberle
Country Director, Indonesia
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Abbreviations, Acronyms and Indonesian Terms

APBN	*Anggaran Pendapatan dan Belanja Negara* (National Budget)
Askes	*Asuransi Kesehatan* (Health insurance for government employees including military and pensioners)
Askeskin	*Asuransi Kesehatan Masyarakat Miskin* (Health Insurance for the Poor)
Bappenas	*Badan Perencanaan dan Pembangunan Nasional* (National Development Planning Agency)
BKKBN	*Badan Koordinasi Keluarga Berencana Nasional* (National Family Planning Coordination Agency)
BLT	*Bantuan Langsung Tunai* (Unconditional cash transfer)
BPS	*Badan Pusat Statistik* (Statistics Indonesia)
BSM	*Bantuan Siswa Miskin* (Cash transfer for poor students)
Bulog	*Badan Urusan Logistik* (National Logistics Agency)
CGH	Coady-Grosh-Hoddinott measure
CPI	Consumer Price Index
EE	Exclusion error (or undercoverage)
GDP	Gross Domestic Product
IE	Inclusion error (or leakage)
IFLS	Indonesian Family Life Survey
Jamkesmas	*Jaminan Kesehatan Masyarakat* (Health Insurance for the Poor)
J-PAL	Abdul Latif Jameel Poverty Action Lab at MIT
JPS	*Jaring Pengaman Sosial* (Social Safety Net)
Kabupaten	District
Kecamatan	Sub-district
Kemdiknas	*Kementerian Pendidikan Nasional* (Ministry of National Education, MONE)
Kemenag	*Kementerian Agama* (Ministry of Religious Affairs)
Kemenkes	*Kementerian Kesehatan* (Ministry of Health, MOH)
Kemenkokesra	*Kementerian Koordinasi Kesejahateraan Rakyat* (Coordinating Ministry of Social Welfare)
Kemenkominfo	*Kementerian Komunikasi dan Informasi* (Ministry for Communication and Information)
Kemensos	*Kementerian Sosial* (Ministry of Social Affairs, MOSA)
LHS	Left-hand side (graph axis that relevant to particular series)
MIS	Management Information System
MOH	Ministry of Health
NTS	National Targeting System
OPK	*Operasi Pasar Khusus* (Special Market Operation)
PD	Project Director
PKH	*Program Keluarga Harapan* (Conditional cash transfer)
PL	Poverty Line
PMT	Proxy Means Testing
PMU	Program Management Unit
PNPM	*Program Nasional Pemberdayaan Masyarakat* (National Program for Community Empowerment)

PPLS	*Pendataan Program Perlindungan Sosial* (Data Collection for Targeting Social Protection Programs)
PPP	Purchasing Power Parity
Ppt	Percentage points
PSE	*Pendataan Sosial Ekonomi Penduduk* (Socio-economic Population Survey)
Puskesmas	*Pusat Kesehatan Masyarakat* (Community health center)
Raskin	*Beras Miskin* (Program for sale of subsidized rice to the poor)
RHS	Right-hand side (Graph axis that relevant to particular series)
Rp	Indonesian *Rupiah*
RPJM	*Rencana Pembangunan Jangka Menengah* (Medium-term Development Plan)
SJSN	*Sistem Jaminan Sosial Nasional* (National Social Security System)
SMERU	SMERU Research Institute (formerly Social Monitoring Early Response Unit)
Susenas	*Survei Sosio-Ekonomi Nasional* (National Socio-Economic Survey)
TNP2K	*Tim Nasional Percepatan Penanggulangan Kemiskinan* (National Team for Accelerating Poverty Reduction)
US$	United States Dollars

Executive Summary

Reaching the Poor and Vulnerable with Social Assistance in Indonesia

Indonesia has seen strong economic growth and falling poverty in the last decade. Yet half of the country gets by on relatively little, and many of these become poor each year. In the last ten years Indonesia has returned to strong economic growth. The poverty rate has fallen from 23.4 percent of all Indonesians in 1999 to 12.5 percent by 2011.[1] However, half of the country still lives on less than Rp 15,000 per day,[2] and small shocks can move them into poverty. Because of this, people move into and out of poverty easily in Indonesia. Of the all poor in each year, over half were not poor the year before; they are newly poor. Over a three year period, a quarter of all Indonesians will be in poverty at least once.

Social assistance, or a social safety net, is vital to protect the 40 percent of Indonesians who are highly vulnerable to poverty. There is a large group of vulnerable households in Indonesia. The poorest 40 percent of Indonesian households this year have at least a one in ten chance of being poor the following year. This chance becomes much higher the poorer they are now. In fact, over 80 percent of next year's poor will come from this group, who live on less than Rp 12,000 per day.[3] The ease of falling into poverty for this vulnerable group means social safety nets are needed protect them, in addition to programs to help the long-term poor out of poverty.

Over the last 15 years, Indonesia has established a first generation of household social assistance programs. There are now a number of household social assistance programs in Indonesia to support the poor and vulnerable. These include subsidized rice (Raskin), health fee waivers (Jamkesmas), cash transfers for poor students (BSM), a conditional cash transfer (PKH), and a temporary unconditional cash transfer (BLT). These programs are designed to promote the poor out of poverty, and protect the vulnerable from falling back in. However, the current programs are only partially effective in achieving this.

Many Indonesians are highly vulnerable; of all the poor in each year, over half are newly poor

There is much to do to improve these programs so that they can better protect the poor and the vulnerable. The World Bank has just completed a major report, *Protecting Poor and Vulnerable Households in Indonesia,* taking a comprehensive look at social assistance in Indonesia. It has three main recommendations. First, find the best mix of programs. This means making effective programs bigger, and reducing or changing those that do not work as well. Second, double spending to 1 percent of GDP in the coming years, so that good programs are expanded and gaps filled in. Indonesia can afford this, with its strong economic health, even more so if the large fuel subsidies which help the rich the most were reduced. Finally, a long-term roadmap is needed to develop a social assistance system, rather than just a collection of programs. This should outline how programs can be integrated to work together better, accelerate poverty reduction, and protect the vulnerable. These efforts can begin with how programs reach the poor.

The Government of Indonesia has committed itself to reforming and integrating social assistance programs as part of its poverty reduction strategy. Reducing poverty is a key concern of the government. President Susilo Bambang Yudhoyono has previously declared it to be his government's highest development priority. The 2009-14 Medium Term Development Plan (RPJM) aims for poverty to fall to 8 to 10 percent by 2014, as well as improvements in social assistance, such as better health services under Jamkesmas. The plan also wants programs to work together better, with a single monitoring system to help make decisions and budgets. These efforts are being coordinated by a new National Team for the Acceleration of Poverty Reduction (TNP2K) led by the Vice President.

1 Statistics Indonesia (BPS) sets the official poverty line for Indonesia, which is defined as the amount of money required to obtain 2,100 calories per day from local food commodities and a small amount for other basic necessities, such as clothing, housing, and transportation. In 2011, the poverty line was around Rp 233,700 per household member per month.

2 Equivalent to around PPP$2.25 a day. This is using the most recent (2005) PPP exchange rate for private consumption of Rp 4,193 per PPP$1, adjusted for CPI inflation to 2011, resulting in an exchange rate of Rp 6,575 per PPP$1. The PPP exchange rate is taken from the World Bank's World Development Indicators, and CPI data from Statistics Indonesia.

3 PPP$1.80.

Current Targeting of the Poor and Vulnerable

One way the government wants to make social assistance work better is to make sure it reaches poor and vulnerable households. For social assistance to work best, it needs to be received by households who need it most. This means identifying not only those who are already poor, but also the many vulnerable households who, while not poor now, can easily become so with a small shock. This could include the poorest 40 percent of Indonesian households, who live at near-subsistence levels. Trying to identify these households is called targeting. An effective way of targeting them increases the chance that they will receive assistance. Improving targeting is an important goal in the RPJM, which calls for a new unified database for targeting.

Current programs, however, targets the poor using different methods. At the moment, social assistance programs in Indonesia all work separately from one another. This is also true of targeting, with each program doing it separately from the others, even when they are looking for the same people. Because different methods are used, each program has quite different beneficiaries. Even though BLT, Jamkesmas and Raskin are aimed at the poorest 30 percent of households, less than one third of these households receives all three programs. Before targeting in Indonesia can improve, how each program is targeted now needs to be looked at, and how well it works.

Indonesia's largest social assistance program, a temporary cash transfer called BLT, tried to compile a list of poor and vulnerable households. BLT was established in haste to protect households against rising fuel prices. As the government reduced fuel subsidies in 2005 in the face of rising fuel prices, it introduced BLT to help cushion the effects on the poor and vulnerable. Statistics Indonesia was asked to compile a list these households in a very short time. A range of methods were planned, but in practice, the potential beneficiaries were mainly suggested by sub-village heads, without a clear basis for nomination. If a poor household was not nominated, they were not assessed, and many of them missed out on the program. When BLT was run again in 2008, largely the same households were revisited, meaning households not on the 2005 list generally missed out again in 2008.

Even though BLT has the best targeting of the major programs, over half of poor and vulnerable households were excluded. BLT aimed to find the poorest 30 percent of Indonesian households. However, only 46 percent of them actually received transfers. At the same time, many households who are better off are included, and in fact they receive half of all benefits. One way to assess targeting performance is to score it on a scale where 0 means no targeting (that is, handing out benefits randomly), and 100 means perfect targeting (all the benefits are received by the poor). Targeting is very hard and never perfect; 50 is a good score. On this scale, BLT scores 24. Despite being the best targeted of the major social assistance programs, if BLT is deployed in the future, targeting can be better.

Jamkesmas also uses a list of the poor, but actual targeting depend on local decisions. As with BLT, many poor households are not reached. Jamkesmas cards should be given to those households on Statistics Indonesia's official list of the poor, such as that for BLT. But how cards are handed out is done differently in different places. Some districts use the official lists, while health officials in other districts select beneficiaries themselves. Even until recently, households could receive Jamkesmas benefits simply with a letter from the village head. These differences in targeting mean poor households have different chances of getting a card in different parts of Indonesia. Similarly to BLT, Jamkesmas covers 45 percent of households it is trying to find, but non-poor households make up 55 percent of all beneficiaries. As a result, the Jamkesmas targeting score is only 16 out of 100, behind that of BLT.

The same households are targeted, but less than one in three receive benefits from all three main programs

Similarly, the targeting of Raskin rice is largely determined at the community level. Sometimes official lists are used but often it is given out as the community sees fit. Like Jamkesmas, Raskin is meant to be given to people on the official lists of the poor, after being checked at a broad-based community meeting. But again, how it is really handed out varies at the local level. Often the community meetings to check the list are not held, or are not open to many members. Often the official list itself is not used, and the rice is distributed as the village head thinks best. Rice is often shared equally among households, poor or non-poor, in order to avoid conflict and tension.

The informal sharing of Raskin means benefits are spread widely across the community. Many poor households receive rice, but the benefits are diluted. Raskin is distributed to nearly twice the number of beneficiaries as planned; 54 percent of all Indonesian households receive some rice. An advantage of this is that 71 percent of target households benefit, which is higher than both BLT and Jamkesmas. However, because of this sharing, poor households get far less than the official 15 kilograms of rice per month, meaning they do not get the help they need. For Raskin, nearly 70 percent of all beneficiaries are not poor, and many are not close to being poor. In fact, around one in six households of the richest 20 percent of Indonesia receive Raskin rice. Raskin's overall targeting score is only 13 out of 100.

BSM also has poor targeting, with a non-poor student nearly as likely to get cash as a poor or vulnerable one. BSM beneficiaries are typically nominated by schools or school committees. Students must have shown good attendance and behavior. Because of this, new students or ones who not yet started have little chance of being selected, nor do those who are not well known to the principal. Poor children who are not in school are not considered at all. Students from the poorest 40 percent of households get about half of all BSM funds, while households in the top 60 percent receive the other half. That is, BSM is nearly as likely to be received by a poor or vulnerable student as by a student in a richer household.

Improving Targeting in Indonesia

Many poor household in Indonesia receive social assistance, but many remain excluded. Some key problems have been identified. For most major programs, poor and vulnerable households are more likely to receive benefits than non-poor households. However, many poor still miss out, and non-poor households get around half of all benefits. After looking at each program's way of targeting and how well it works, several key problems have been found. There are problems in the design, implementation and coordination of targeting.

Targeting outcomes can be improved if methods are better designed. Deciding which households to include in the selection process is very important for targeting, since a poor household who is not even considered in the first place will not become a beneficiary, no matter how well households are be assessed. In Indonesia, many poor households are not considered for social assistance. As discussed, half of the households BLT was trying to find were not nominated by community leaders. Once potentially poor and vulnerable households are included in the initial targeting process, the next step is selecting the right ones. This has not always been done well in Indonesia, as with the frequent sharing of Raskin rice evenly among all households, regardless of poverty.

Targeting methods also depend on successful implementation. A major problem has been a lack of awareness. How targeting is actually done is as important as how it is designed. Well-planned targeting will not work if it is not executed successfully. In addition official targeting guidelines not being followed in the field, targeting in practice has suffered from poor socialization and a lack of coordination between agencies and programs. Socialization – making all stakeholders aware of a program's purpose and intended beneficiaries, their rights and responsibilities – has not been done well for most programs. As a consequence, who receives benefits and why has not been clear and official targeting processes are not followed. It increases the possibility of corruption, and can lead to conflict and tension in communities.

Greater coordination between programs would improve both targeting and program effectiveness. There are two ways in which programs can work together to improve the impact of social assistance. First, some functions would work better if coordinated across programs, such handling program complaints from households in the same place and conducting program awareness campaigns together. This also applies to targeting. Programs with objectives that overlap can make sure that poor households who receive one program also receive the other. For example, PKH would be more effective if its beneficiaries also received Jamkesmas, as the promotion of healthy behaviors would be supported by free health care. Up until now, this has not been done. One reason is that there are no clear arrangements to help programs and agencies work better together.

Building a National Targeting System

Targeting in Indonesia could be made more effective by building a National Targeting System. At the heart of a National Targeting System (NTS) is a unified registry of poor and vulnerable households. This has already been done in other countries, including Chile, Colombia, Mexico, and the Philippines, and has several benefits. The unified registry can be built using the best targeting methods, providing quality data for all programs, at a lower cost. From this registry, each program can use its own criteria to get beneficiary lists which include more poor families, and less non-poor. What is more, the registry can tell any program what other social assistance a household is getting, so that programs can work together better. Having all households who receive social assistance in the same database also means that duplication, fraud and corruption can be reduced. The registry can also be used to link with other government efforts, such as trying to bring more poor families into the banking system, or teach them more about using fertilizer and newer seeds.

Deciding whether social assistance provides the right benefits is easier when program beneficiaries are chosen from the same registry. When most programs are targeted with the NTS, it is natural to think about the benefits received as a whole. Who can get more than one program? Does the mixture of benefits add up to a sensible support package? Or do some programs overlap, at the same time as there are gaps in protection? These are important questions for designing an effective approach to social assistance. Building an NTS can help start discussion within government and supporting parties.

Indonesia has already made good progress on building a unified registry of poor and vulnerable households. A unified registry has already been mandated in the RPJM, with a Presidential Instruction outlining the steps required. Considerable progress has already been made. In 2011, Statistics Indonesia conducted PPLS11, a very large-scale updating of its list of poor households. This is a significant expansion from previous lists, increasing the number of households surveyed from around 19 million in 2008 to 25 million, covering around 45 percent of the population. A broad range of demographic data were also collected, to help target different programs. Most importantly, in 2011 the previous list was not simply revisited, as it largely was in 2008; instead, all households in Indonesia had a chance of being assessed. This meant that new households could enter the list, and previously poor households who have exited poverty could graduate off of it. The many strengths of PPLS11 make it a good basis for the unified registry.

The unified registry is an important part of an NTS, but is only part of a broader system. PPLS11 is a solid start towards building a unified registry and an NTS to support it. However, there is much left to do. To begin with, the unified registry needs to be constructed from the PPLS11 data, which has significant information technology requirements. Beyond the unified registry, there are three key imperatives for the NTS. It needs to *reach the right people*. It needs to *stay current*. And it needs to be *managed well*.

A unified registry will provide beneficiary lists which include more poor families

Improving targeting in Indonesia begins by reaching the right people. Reaching the right people means three things for targeting. First, the right people means not just the poor, but also the vulnerable. Reducing poverty in Indonesia means not just helping the chronic poor, but also protecting the many vulnerable households from falling into poverty. Second, to reach these people, the right targeting methods need to be used, with attention paid to both design and implementation. Third, the unified registry must be used by all programs to ensure the right people are being reached. Using the new registry will help make targeting more consistent, help programs work together better, and allow better monitoring of outcomes.

The unified registry needs to stay current because of the fluid nature of poverty in Indonesia. Household and family circumstances change frequently. There are many non-poor households in Indonesia who can easily fall into poverty if they suffer a health, employment, or of other type of shock. At the same time, economic growth, improving access to services, and hard work are lifting many poor households out of poverty. Over time, they will no longer need the long-term assistance aimed at the chronic poor. To allow social assistance adapt to this frequent entry and exit from poverty, the NTS needs to stay current. Staying current also means adapting to non-economic changes in households, such as the birth of a child or a change of address. Consequently, updating the registry is vital. One way this can be done is by allowing households to appeal if they have not been assessed correctly or their circumstances have changed.

Recent field experiments demonstrate that incorporating a well-designed and facilitated role for communities in targeting can increase both accuracy and community satisfaction, as can self-targeting. They also show that self-targeting methods– where households apply directly – can bring in those poor not currently receiving benefits. Using community-based methods and self-targeting are promising mechanisms for updating and appeals.

The NTS also needs to be managed well. The effectiveness and legitimacy of the NTS depend upon it being well managed. This means it needs to be accountable, transparent and participatory. To do this, the main long-term challenge for the NTS is deciding its institutional framework. Does the coordination role stay with TNP2K, does it become an independent agency, or is it moved to a more established central ministry? Where can complaints be filed, and how will they be resolved? Who will conduct updating activities? Who will conduct awareness campaigns, and coordinate them across programs? Answering these questions will help with the good governance of the system. For example, to promote accountability, the NTS could report to a steering committee of relevant government ministries and agencies. Broader participation can be promoted if civil society, communities and NGOs help monitor and evaluate targeted programs at the local level, and contribute to updating and appeals. Substantial improvement in socialization to all parties will not only help improve targeting implementation and outcomes, but also transparency and legitimacy.

Experiments show that statistical methods target the poor well, but community and self-targeting methods can help find the very poor

Building an NTS is only a small part of the cost of social assistance. About 4 percent of total government spending goes to household social assistance, or around Rp 25.2 trillion (US$ 3 billion) in 2010. This can rise as high as 7 percent in times of significant crisis. An NTS can help make this spending more effective by making sure it is received by those who need it most. Furthermore, it is cost-expensive to develop. The cost of building and maintaining the NTS would be only a small part of the total cost of each social assistance program. Constructing the unified registry will cost about Rp 600 billion. This would be around 4 percent of Raskin's total costs, 12 percent for Jamkesmas, or 2 percent for BLT. However, because the NTS can be used by all three programs, the initial costs would only be just over 1 percent of the three combined annual program costs. Ongoing costs each for maintaining the system are likely to be lower, but even at the same level, total annual targeting costs remain very low relative to the total cost of benefits transferred.

Indonesia is showing global leadership in the targeting social assistance, as it tests innovative ways to involve communities and poor households. As Indonesia continues to develop as a middle income country, it has the capacity to improve social assistance, reduce poverty and protect the vulnerable. Strong economic growth in the last forty years has seen Indonesia join the ranks of middle income countries, and good progress has been made in poverty reduction. Nonetheless, improvements in social assistance are needed to protect the many vulnerable households that remain. Targeting is key to these efforts. Indonesia has the financial and administrative capacity to make targeting better, both by learning from other countries and leading the way into new areas. With its innovative piloting of new ways for involving communities and poor households in the process, Indonesia is playing a global role in extending the knowledge frontier of social assistance policy. Access to social assistance through better targeting means that climbing out of poverty, and being protected from falling back in, can become a reality for the millions of Indonesians who still struggle in their daily lives. Important steps have been taken, but care must be taken not to lose focus on the considerable amount of work still to be done.

Introduction

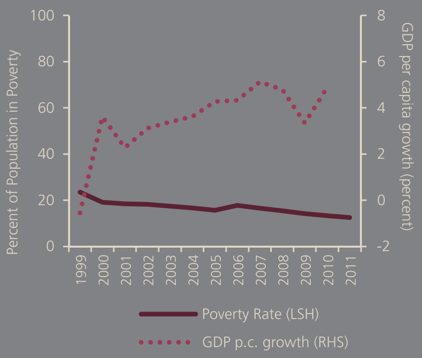
Poverty, Vulnerability and Social Assistance in Indonesia

Despite strong economic growth and falling poverty in the last decade, progress in key health and education indicators remains sluggish. The last decade in Indonesia has seen a return to strong economic growth, and the poverty rate has fallen from 23.4 percent in 1999 to 12.5 in 2011 (Figure I.1). However, improvements in junior and senior secondary school enrolment rates have been slow, and malnutrition (stunting) has remained stubbornly high (Figure I.2). Despite primary school enrolment of over 90 percent, secondary enrolment rates have risen slowly and senior secondary school enrolment has struggled to reach 50 percent. 36 percent of all children remain stunted in 2010, close to its 2005 level of 39 percent. Infant and child mortality have seen only modest decreases and remain high for the region.[4]

4 Only Cambodia (91) and Lao (70) have higher rates than Indonesia in 2007, with the Philippines (28), China (22), Vietnam (15), Malaysia (11) and Thailand (7) all lower (UNICEF).

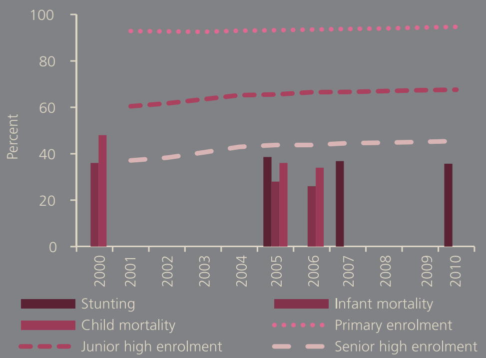
Despite strong economic growth and falling poverty over the last decade, progress in key social indicators remains sluggish.

Figure I.1: Per Capita GDP Growth and Poverty



Sources: BPS.

Figure I.2: Health and Education Indicators



Source: World Development Indicators, Susenas, Riskesdas. *Notes*: Stunting is <-2 standard deviation height-for-age z-score. Enrolment rates are net.

Although poverty levels are relatively low, much of the population lives clustered just above the poverty line. In 2011 12.5 percent of households lived below the national poverty line of Rp 233,700 per person per month (around PPP$1.19 per day).[5] However, as Figure I.3 illustrates, much of the Indonesian population is clustered just above this line, with around 24 percent below the official near poor line of 1.2 x the poverty line, 38 percent below 1.5 x the poverty line, and nearly 60 percent below 2 x the poverty line (Table I.1). Thus living standards remain low for many Indonesians, and relatively small shocks to their income and consumption can send them into poverty.

Although poverty levels are relatively low, much of the population is clustered just above the poverty line.

Figure I.3: 2011 Per Capita Convnvvsumption Distribution

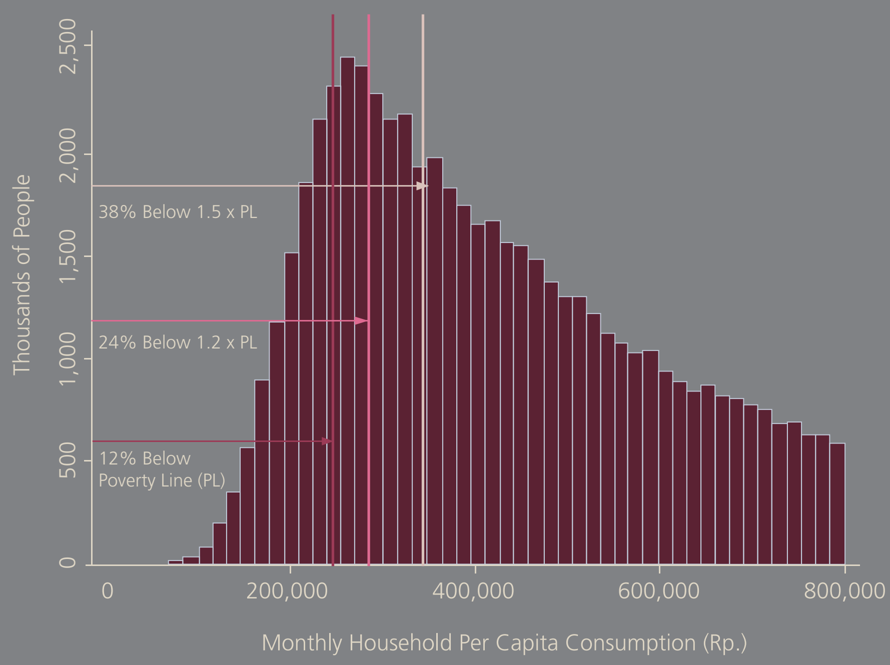


Table I.1: Population Below Multiples of the Poverty Line, 2008-2011

	Poverty Rate (%)			
Poverty Line (PL) Multiple	**2008**	**2009**	**2010**	**2011**
0.8 x PL (~$PPP 0.95)	6.0	5.3	4.6	4.3
National PL (~$PPP 1.20)	15.4	14.1	13.3	12.5
1.2 x PL (~$PPP 1.42)	27.8	25.6	24.4	23.8
1.5 x PL (~$PPP 1.78)	43.1	42.6	39.4	38.4
1.8 x PL (~$PPP 2.13)	56.9	56.5	51.3	49.9
2.0 x PL (~$PPP 2.37)	64.3	63.9	58.0	56.5
2.5 x PL (~$PPP 2.96)	77.2	76.8	70.6	68.5

Sources: Susenas
Notes: The national poverty line is around Rp 233,700 per person per month in 2011. 1.2 x PL is the official near poor line. See footnote 15 on estimates of Purchasing Power Parity rates.

5 This is using the most recent (2005) PPP exchange rate for private consumption of Rp 4,193 per PPP$1, adjusted for CPI inflation to 2011, resulting in an exchange rate of Rp 6,575 per PPP$1. The PPP exchange rate is taken from the World Bank's World Development Indicators, and CPI data from Statistics Indonesia.

Moreover, the declining annual poverty rate hides the high rate of new poverty, with over half of the 2010 poor newly entering poverty that year, and a quarter of the population having been in poverty at least once in the last three years. The falling poverty rate understates the high exit and entry to poverty that exists in Indonesia. In 2010, 12.6 million people who had not been poor in 2009 entered poverty, making up 55 percent of all poor in 2010. 47 percent of all official near-poor in 2010 had been above the near=poor line in 2009 (Figure I.4).[6] In fact, in the three years from 2008-10, a quarter of all Indonesians have been in poverty for at least one of the last three years, and 43 percent at least once below the near poor line (Figure I.5). However, a high degree of new entry into poverty combined with a falling overall poverty rate means that there is also a high degree of exit out of poverty for many households in any particular year. Consequently, if the rate of entry into poverty could be substantially reduced, while current exit rates from poverty maintained, overall poverty would fall much faster compared to recent rates.

Despite overall poverty falling, many non-poor fall into poverty each year, making up over half of all poor. A quarter of the population was poor at least once in the last three years, and 43 percent were near poor.

Figure I.4: New and Existing Poor in 2010

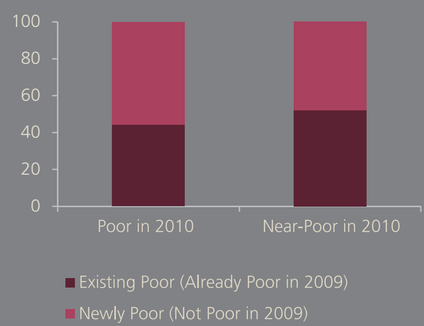
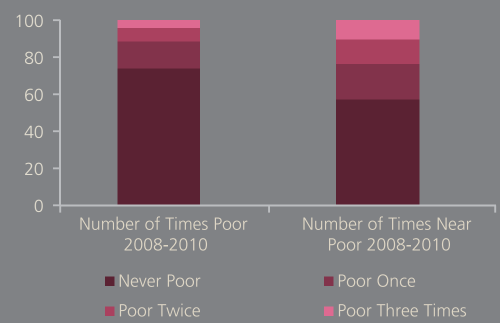


Figure I.5: Number of Years Poor or Near-Poor in Last Three Years for All Population



Sources: Susenas and World Bank calculations.
Notes: 'Poor' are people with monthly per capita consumption below the national poverty line (around Rp 211,000 in 2010), and 'near-poor' line are people below 1.2 times the poverty line. 'Newly poor' people represents the percentage of all poor who were not poor last period. 'Years Poor' is the number of years between 2008 and 2010 a person was in poverty.

Around 40 percent of Indonesians remain highly vulnerable to poverty. Combined with the slow progress in health and education, this underscores the importance of social assistance and social safety nets. There exists a large group of vulnerable households in Indonesia. Those in the poorest 40 percent of Indonesian households this year have at least a 10 percent chance of being below the poverty line in the following year, with this chance being much higher the poorer they are now. In fact, over 80 percent of next year's poor will come from this group, who have a per capita consumption below 1.5 x the poverty line (around PPP$1.78 per day). The high incidence and rate of entry into poverty of this vulnerable group, combined with stagnating social indicators, underlines the importance not only of policies and programs promoting the chronically poor out of poverty, but also of social safety nets which protect the vulnerable from falling back into poverty.

Indonesia already has a range of household social assistance programs in place, including Rice for the Poor (Raskin), intended to provide a measure of food security for poor and the vulnerable. A subsidized rice program for the poor has existed in Indonesia in some form since the 1997-98 Asian Financial Crisis.[7] Under the current program, the National Logistics Agency (Bulog) purchases rice from wholesalers using a subsidy from the Government of Indonesia. The rice is then distributed to villages, where eligible households can buy up to a set quantity of rice at considerably less than market price. Recipient households are officially meant to buy up to 15kg of rice per month at Rp 1,600 per kg. Retail rice prices were Rp 9,300 per kg in 2011, meaning that the level of government subsidy is substantial.[8] Raskin and the other programs are summarized in Table I.2.

6 Statistics Indonesia use 1.2 x the poverty line to define the near poor. The poverty line itself is defined as the money required to obtain 2,100 calories per day from local food commodities and a small amount for other basic necessities, such as clothing, housing, and transportation.

7 It was previously known as the Special Market Operation (OPK), which was part of the Social Safety Net (JPS) implemented during the crisis.

8 See World Bank (2012f) for a detailed review of Raskin.

There are a range of household-targeted social assistance programs in Indonesia.

Table I.2: Major Household Social Assistance Programs in Indonesia (2010)

Name	Transfer type	Target group	2010 target number of recipients	2010 coverage	2010 benefit level	Total 2010 budgeted expenditures (Rp Billions)	Key executing agency
BLT*	Cash	Poor & near-poor households	18.7m households (HH)	National	IDR 100,000 per month for 9 months	17,700 – 23,100**	Ministry of Social Affairs (Kemensos)
Raskin	Subsidized Rice	Poor & near-poor households	17.5m HH	National	14 kg rice per month	13,925	Bureau of Logistics (Bulog)
Jamkesmas	Health service fees waived	Poor & near-poor households	18.2m HH	National	Varies depending on utilization	5,022	Ministry of Health (Kemenkes)
BSM	Cash & Conditions	Students from poor households	4.6m students	National, but not full scale	Rp. 561,759 per year	2,904	Ministry of National Education (Kemdiknas) & Ministry of Religious Affairs (Kemenag)
PKH	Cash & Conditions	Very poor households	810,000 HH	Pilot	IDR 1,287,000 per year	1,300	Kemensos

Source: World Bank (2012d). *During last usage in 2008-09. ** Total expenditure for nine months across 2008 and 2009 (17,700 bn) and for twelve months across 2005 and 2006 (23,100 bn).

In addition, there is a Health Insurance for the Poor (Jamkesmas) program, to mitigate health shocks. As the government substantially reduced public fuel subsidies in the face of rising prices in 2005, it introduced two safety net programs, Askeskin and BLT (discussed next), to mitigate the impact of price increases on poor and near-poor households. Askeskin, a free health care program, aimed at making basic health services available to beneficiary households. Run by PT Askes, beneficiary households received health cards entitling them to free healthcare at local public health clinics and in-patient treatment in third-class public hospital beds, as well as obstetric services, mobile health services, immunizations and medicines. The program is tax-financed by the central government and does not require any insurance contributions or cost-sharing on the part of beneficiaries or local governments. In 2008 Askeskin was renamed Jamkesmas, being essentially the same program but with expanded coverage, and is currently run by the Ministry of Health.[9]

A temporary unconditional cash transfer (BLT) is designed to assist the poor and near poor in times of high food and fuel prices. BLT was also introduced in 2005 in response to fuel subsidy reductions, under the Ministry of Social Affairs (Kemensos) and targeted by Statistics Indonesia. It ran for 12 months from late 2005 to 2006, with beneficiary households receiving Rp 300,000 every three months. This represented about 15 percent of the poverty line. The program was intended as a temporary one-off assistance program during a time of inflationary pressures on the poverty basket and ended in the second half of 2006 as fuel prices retreated. With fuel and food prices increasing sharply again during 2007-08, the government responded by initiating a second round of BLT in 2008-09.

A range of scholarship initiatives, collectively known as *Beasiswa untuk Siswa Miskin* (BSM) provide cash transfers for school attendance. The BSM programs provides transfers from central agencies responsible for education directly to students or the schools at which students study. Scholarships are provided by both Ministry of National Education (Kemdiknas) and Ministry of Religious Affairs (Kemenag), contingent on enrollment, attendance and other criteria.[10] The amount of the transfers provided rises with the level of education, from Rp 360,000 for primary school to approximately Rp 1.2 million (per year) for a university student. The BSM program is actually 10 independently-run initiatives that together cover all levels of education (including vocational education) at secular and religious public schools.

9 See World Bank (2012g) for a detailed review of Jamkesmas.

10 See World Bank (2012h) for a detailed review of BSM.

Unlike other household-based transfers, the BSM initiatives have neither a central coordinating unit nor a unified budget. Within each institution, separate units independently manage and execute initiatives for students from each level of schooling and for vocational education. The Kemenag-run BSM initiatives for university scholars are further fragmented by religion. The 10 BSM initiatives have their own separate manuals, fund flow structures and implementing procedures with little coordination between initiatives, even among those located in the same institution.

Finally, a conditional cash transfer program (PKH) has been piloted, to help the chronically poor invest in the human capital of their children and promote them out of poverty. PKH provides direct cash benefits conditional on household participation in locally-provided health and education services. The two main components – a cash transfer and monitored conditionalities – provide an immediate impact on household poverty while encouraging investment in long-term household productivity. The PKH cash transfers range from Rp 600,000 to Rp 2.2 million per year (depending on the number of qualifying dependents in the household) and they are delivered four times per year. The direct household budget support is delivered only after a mother's verified attendance at pre- and post-natal checkups, a professionally-attended birth, newborn and infant weighings and health checks, and after verification that school-aged children have good attendance records at their schools. In 2010, PKH reached 816,000 very poor households in 25 out of 33 provinces (118 out of 497 districts), with plans to expand to 3 million households nationally by 2014. PKH is implemented by Kemensos with funds disbursed to households through the local post office.[11]

However, improvements are needed in current programs and cross-program coordination, and additional programs are required to protect the vulnerable. In a companion to this report, the World Bank (2012d) has just completed a comprehensive review of social assistance program effectiveness and funding, *Protecting Poor and Vulnerable Households in Indonesia*, which includes three key recommendations. First, spend better to achieve a more optimal mix of welfare-improving programs, by scaling up or institutionalizing cost-effective programs, rationalizing those that deliver too little at too high a cost, and re-engineering programs that are struggling to deliver benefits to those most in need, as well as improving access to services. Second, as reforms are implemented, spend more on cost-effective programs and remaining gaps, aiming to double spending to 1 percent of GDP over the medium term. Indonesia's strong fiscal position, which could be strengthened with additional subsidy reduction, makes this increase affordable. Finally, develop a long-term reform roadmap to establish and sustain a comprehensive social safety net. This may involve consolidating programs under a single system and transforming agencies to accelerate poverty reduction and protect the vulnerable. Such efforts could begin with integrating program targeting of beneficiaries and benefits.

Not all households can be covered by these programs at current and expected future budget levels. Thus targeting is important in trying to channel non-universal benefits to those households who need it most. Although many people are vulnerable to shocks and falling into poverty, with limited social spending budgets, not all households can be covered by social assistance and protection programs. The major programs target the poorest 25 to 30 percent of households, with daily per capita consumption below around Rp 280,000, which is only 20 percent above absolute subsistence levels.[12] Moreover, as discussed, the poorest 40 percent of Indonesian households remain highly vulnerable to falling into poverty. An effective means of targeting can increase the likelihood that these people receive public assistance.

Targeting must also distinguish between the chronic poor who require assistance to move out of poverty, and the broader group of Indonesian households most vulnerable to poverty, who require protection to prevent them from falling into poverty. Targeting in Indonesia has multiple objectives. The poor and the vulnerable are not always the same people, and programs might have different target criteria such as malnutrition or under-enrolment. Consequently, Indonesia needs to be able to target both the chronic poor with programs designed to promote themselves out of poverty, such as conditional and unconditional cash transfers, and the vulnerable with programs designed to help them avoid or mitigate shocks, as well as having broader programs designed to ensure universal access to basic services such as health and education.

Indonesia represents a complex environment for successful targeting. Nearly 240 million people are dispersed across some 18,000 islands, making Indonesia the world's fourth largest country by population and the largest archipelago. In addition, in 2000-01, Indonesia decentralized considerable budgetary and operational control to the district level; there are currently nearly 500 districts. Given the fluid nature of Indonesian poverty already noted, with high rates of entry and exit, targeting has multiple requirements, having to distinguish between the different consumption

11 See World Bank (2012i) for a detailed review of PKH.

12 Major programs target the near-poor and below, which are those households below 1.2x the national poverty line. The poverty line is set as the amount required to obtain 2,100 calories per day from local food commodities and a small amount for other basic necessities, such as clothing, housing, and transportation.

levels, as well as chronic poverty and transient poverty. A lower inequality of consumption in Indonesia compared to other countries, notably in Latin America, makes distinguishing between the poor and near-poor more difficult.[13] Thus, the large population, geographic dispersion, and decentralized structure, combined with lower inequality and multiple program targeting objectives, means that targeting in Indonesia is difficult and complex.

The high degree of fragmentation in the delivery of current social assistance also affects targeting. Integration of social assistance programs and systems is a government priority, with targeting one of the main focuses. In addition to improved individual program design and delivery, as well as a better spending mix, the World Bank (2012d) review of social assistance programs also found a high degree of fragmentation in the current approach, with many different implementing agencies and no common systems or methodologies. The government has recognized this and has made integrating social assistance programs a priority. Reforming and coordinating the targeting of programs is one of the main mechanisms that has been identified to help unify the programmatic approach.[14]

Indonesia has recently begun moving towards a social insurance framework with universal coverage, based on a mix of contributions from non-poor households and public funding of contributions targeted at the poor and vulnerable. In 2004, the government of Indonesia passed the National Social Security Law (SJSN law). This law established five social insurance funds that would eventually cover all Indonesian workers in both the formal and informal sectors. This represents Indonesia's intention to move toward a more comprehensive coverage of 'life-cycle' risks, providing insurance protection against health risks, worker accident and death, and retirement protection through a combination of life annuities and old-age savings. According to the SJSN law, the government will pay contributions for the poor, so targeting remains important under the new framework. The vision presented by the SJSN law recognizes that Indonesia is becoming a middle-income country and that many workers now have discretionary income that can be used to help finance broader social protection. Nonetheless, this transition will need to take place over a period of decades, given the many Indonesians who live just above the poverty line and remain vulnerable to falling into poverty.

The short- to medium-term political economy outlook suggests that continued expenditures on social programs targeted at the poor and vulnerable will remain the norm for the next decade. Consequently, this report focuses on improvements in poverty targeting in Indonesia. There are a number of reasons to think that the current approach to social assistance will remain an important component of Indonesia's social protection system in the immediate future. First, movement towards universal social insurance has been very slow. The SJSN law was passed in 2004, but implementing regulations were only just passed at the end of 2011, with implementation not beginning until 2014. Thus, targeted programs for the poor and vulnerable (and later targeting of government contributions to SJSN for the poor) will remain important for the foreseeable future. Second, given the coming implementation of the SJSN framework, Indonesia is unlikely to move towards a universal non-contributory life-cycle approach to social protection any time soon, under which targeting is much less important (see Box I.1). Furthermore, with such an approach, government expenditures are often around 10 times higher than social assistance targeted at poor and vulnerable groups only. Indonesia currently spends only 0.4 percent of GDP on household-based social assistance programs, below both regional and international averages (World Bank 2012d). Movement to much higher (and untargeted) social expenditures is unlikely to occur in the next decade, especially with the present commitment to spend 20 percent of central government expenditures in the education sector. More likely, given the Indonesian experience since 2005 and current policy environment, there could be a phased reduction in the regressive fuel and energy subsidies which account for around 15 percent of all government expenditures,[15] with some of the savings being channeled into increased spending on targeted household social assistance programs. As a consequence, the focus of this report is specifically on how this assistance can be targeted, rather than a more general discussion of how social asisstance strategy in Indonesia should evolve in the future.

13 The Data Annex contains average household consumption per capita by decile.

14 See the 2009-14 Medium-term Development Plan (RPJM).

15 The 2011 Revised National Budget saw spending on energy subsidies increase Rp.59 trillion to Rp.195 trillion, out of a total of central government expenditure of Rp.1,297 trillion (World Bank 2012j).

Box I.1: An alternative to programs targeted at poor and vulnerable groups is a more universal approach to managing life-cycle risks.

The poor may benefit from two different types of social programs. The focus of this report is on programs targeted at poor households. However, an alternative approach is universal program eligibility for all households within certain demographic categories, regardless of economic means. Such an approach has been termed 'universal' or 'categorical' targeting, or a 'life-cycle risk' approach, and is typified by non-contributory state pensions to all individuals above a given age, or grants to families with children below a given age. Examples exist in Eastern Europe and Sub-Saharan Africa (see Regional Hunger and Vulnerability Program (2010) on the latter).

As all households with demographically eligible members can receive these universally targeted programs, they are associated with two key features. First, generally speaking, many fewer poor households are excluded from universal programs, relative to poverty-targeted programs, as poverty targeting inevitably results in errors of beneficiary selection, which can often be quite high. Second, universal programs tend to represent considerably higher public expenditures. Whether the overall benefit to poor households is greater under one system or another is a matter of debate. Other possible advantages of a universal approach could include easier implementation, reduced social stigma for program beneficiaries, reduced moral and incentive costs, and broader political support (see Section 4 of this report for further discussion).

Which approach is selected depends on local political, social, economic and institutional factors. However, as countries become more developed, there has often been a progression from poverty-targeted programs to universal social assistance programs, which may result from increasing tax revenues and greater democratization (Pritchett 2005). This suggests that neither approach is necessarily best for all countries at all times.

Targeting Poor and Vulnerable Households in Indonesia

The *Targeting Poor and Vulnerable Households in Indonesia* report aims to examine how future social assistance in Indonesia can best targeted at the poor and vulnerable, with three main objectives in mind. This report aims to outline a National Targeting System that can be used by all household-targeted safety net programs, with a unified registry of potential beneficiaries at its core. There are three objectives for such a system: (i) improved targeting methods leading to more accurate identification of beneficiaries for all targeting objectives; (ii) improved program information and education (socialization) for, and buy-in from, all levels of stakeholders; (iii) implemented in a feasible and cost-effective manner.

To meet these objectives, the first part of this report assesses the state of current targeting in Indonesia, while the second part examines how it could be improved. Following immediately after this introduction, Part A of this report discusses how targeting is currently performed in Indonesia, and how effective this is. Part B examines how targeting could be improved in Indonesia, focusing on how a National Targeting System could be developed in Indonesia. Various supplementary materials follow after the the main report.

Part A begins by examining how targeting is currently done in Indonesia. Each social assistance program in Indonesia uses a mix of different targeting methods to identify beneficiaries. Understanding how each program collects data on potential recipients and assesses them is an important step in evaluating current practices. Moreover, comparing official targeting guidelines with actual targeting practices, and identifying reasons for deviations, provides insights into the political, social and institutional context within which targeting in Indonesia occurs. The critical issue of how program objectives, intended beneficiaries and targeting methods are communicated to all stakeholders is also examined.

The accuracy of current targeting is assessed. Assessing targeting outcomes for major programs allows us to evaluate how effective current methods are in practice, what potential scope there is for improvement, and provides a benchmark against which to measure future targeting performance. In this section different measures of targeting outcomes are introduced and their relative merits discussed, before the outcomes of each of the three main programs are assessed, including variation in these outcomes across regions, gender, and urban and rural locations.

How community might best be involved in targeting in Indonesia is also examined. Communities have been involved in the targeting of all three major programs, but the nature of that involvement has often contributed to targeting and program outcomes being less effective than they might otherwise have been. New evidence is presented from field experiments in Indonesia which indicates roles for community involvement which might both improve targeting outcomes and increase community satisfaction.

Part A concludes by looking at how targeted programs are reported and perceived, and how this might affect buy-in. Stakeholder buy-in at all levels – central government and line ministries, local government and community leaders, beneficiaries and the general public – is critical to ensuring political and social support for social assistance programs. Buy-in is dependent in part upon public perceptions and satisfaction, which are in turn driven by media reporting and the experience of program implementation and targeting in communities. Part A concludes with some evidence on media and public perceptions of targeted social assistance in Indonesia.

Part B begins by summarizing the lessons learnt from current targeting in Indonesia and identifying steps required to improve it. The second main part of this report presents a summary of the main lessons from Part A, and identifies what steps can be taken in the future to improve targeting in Indonesia. The recent 2011 large-scale survey of the poor is also discussed, and the role it might play in improved targeting outcomes in the future.

The majority of Part B proposes, outlines and discusses a National Targeting System, with a unified registry of potential beneficiaries at its heart. A National Targeting System is proposed to improve targeting outcomes in Indonesia. The advantages of such a system are briefly examined, as well as possible disadvantages and political economy considerations. The majority of Part B focuses on selected issues of design, implementation, and maintenance and updating of this system, such as the legal and institutional framework required, extraction of beneficiary lists from the unified registry, complaints and grievances, and recertification of the registry.

Accompanying material after the main report includes a data annex and four technical annexes. Collected at the end of the report are supplementary materials. Included are data tables and four technical annexes. The first technical annex discusses the measurement of targeting outcomes, while the second provides greater detail than the main report on how proxy means testing (PMT), an increasingly popular but highly technical approach to targeting, might be optimally deployed in Indonesia. The third and fourth provide details on historical PMT design in Indonesia.

Part A

Current Targeting in Indonesia

01

Targeting Theory and Practice in Indonesia

1.1 Targeting Methods: Advantages and Disadvantages

Targeting requires determining which households to assess. Unless all households are assessed (a survey sweep), some method must be used to choose which households to assess. That is, a *data collection* method must be chosen. There are a number of methods besides survey sweeps for determining which households to collect data from. Geographic targeting, or poverty mapping, uses differences in location characteristics to either determine which areas to survey, or how many households in each area to survey. Pre-existing lists of the poor or program beneficiary lists can be revisited or form the basis of a survey listing. Referrals of households to survey can come from community nominations, whether from just the village head or a meeting of the elite, or from a broader meeting of the whole community. Finally, self-assessment can be used; anyone who thinks they are eligible for assistance can apply for assessment, on the basis that the costs of applying are less for the poor than the non-poor, or the value of the benefits greater.

Targeting also means determining which of these households are poor or vulnerable. Once data have been collected on a number of households, it must be determined which ones are poor or otherwise eligible for social assistance. Again, other than simply selecting everyone, there are a range of *selection* methods for identifying beneficiaries. Widely used in developed countries are verified means tests, where household or individual income is used directly to determine program eligibility, based on recognized documentation. More common in developing countries are proxy means tests, which use statistical techniques to estimate household income or consumption from a set of easily observable and difficult to manipulate household characteristics. Beneficiaries can be selected categorically: for example, all people in a certain age range, or with disabilities, or all households with female heads. Again, the community can select which households become beneficiaries themselves, whether by the community elite or the wider community. Finally, households can self-select – all those applying for benefits receive them, again, with the opportunity cost assumed to be less for the poor.

Each of these methods has advantages and disadvantages, with no single method best for all situations. These different methods have different strengths and weaknesses, and can be better suited for different targeting objectives or contexts than the others. Some of the advantages and disadvantages of the various collection methods are discussed in Table 1.1, while advantages and disadvantages of selection methods are covered in Table 1.2. A targeting approach can in fact adopt a mix of different methods, depending on the circumstances, such as what or who is being targeted, the local conditions, and the targeting and implementation capacity of government. For example, geographic targeting can be used to identify the poorest areas, a survey sweep of all households in these areas is conducted, and proxy means testing used to select beneficiaries. Pre-existing or new lists of the poor can be verified by the community, who can add and subtract names to determine the final list. Households can also apply for assessment, and all those with key demographic characteristics, such as elderly and children, could qualify for programs. A comprehensive and internationally comparative account of targeting methodologies, their implementation considerations, and when they are most appropriate, can be found in Coady, Grosh and Hoddinott (2004).

Each data collection method has different advantages and disadvantages.

Table 1.1: Data Collection Methods: Advantages and Disadvantages

Method	Advantages	Disadvantages
Survey Sweep	▪ Minimizes chances of excluding target households from assessment	▪ Expensive to conduct in all areas (amounts to a census)
Geographic Targeting	▪ Administratively simple ▪ May be politically popular ▪ Easy to combine with other methods ▪ Ensures relative quotas are fair between areas ▪ Accurate if based on good underlying data	▪ Requires good national socio-economic survey data ▪ Less accurate at local levels ▪ Often needs to be combined with a second collection method
Community	▪ Uses local knowledge of household economic status ▪ Allows communities to define need as they see appropriate ▪ Useful for making sure newly poor are included ▪ Potentially better community buy-in	▪ Risk of elite capture ▪ Communities may use different criteria than government or program intends ▪ Concept of community may be difficult in urban areas ▪ Communities may wish to avoid dissent or impose social and religious norms ▪ May conflict with primary community role
Pre-existing Lists	▪ Low cost ▪ Potentially better line ministry and existing beneficiary buy-in	▪ Perpetuates historical targeting error – poor households excluded last time will be excluded this time ▪ Does not allow for changing household circumstances
Self-targeting	▪ Administratively simple ▪ Potentially lower costs ▪ Automatic exit criteria ▪ Has good results internationally for public works or workfare programs ▪ Can maintain work incentives	▪ Historically effective only for public works or workfare programs ▪ Public works programs are not administratively simple ▪ Work requirements and wages are not applicable to many programs ▪ Stigma or time costs may discourage the poor from applying

Source: Adapted in part from Coady, Grosh and Hoddinott (2004)

Each beneficiary selection method has different advantages and disadvantages.

Table 1.2: Selection Methods: Advantages and Disadvantages

Method	Advantages	Disadvantages
Verified Means Testing	▪ Strong targeting accuracy	▪ Depends on reliable information on income or consumption at a reasonable cost ▪ Costs of evidence often shifted to applicant ▪ Can create work disincentives ▪ Generally used in high- and middle-income countries
Proxy Means Testing (PMT)	▪ Relatively accurate targeting outcomes ▪ Easier to verify than means-testing, and difficult to manipulate if designed carefully ▪ Replicable judgments with consistent and visible criteria	▪ Better for long-term poor rather than newly poor ▪ Does not allow for flexibility in assessing households ▪ Has built-in statistical error ▪ Requires relatively high administrative capacity
Categorical (Demographic)	▪ Usually easy to verify ▪ Can be combined with other methods ▪ Often has lower administrative costs ▪ Often targeted at non-working groups, so may not reduce work incentives ▪ High political acceptability ▪ Has very low exclusion rates of both categorically-eligible households and poor households within targeted category	▪ Demographics correlate poorly with poverty ▪ If broad categories are used, exclusion rates amongst the poor are low, but program costs are much higher than other methods of targeting the poor ▪ Young and old may be less mobile (and therefore require outreach) ▪ Identification often lacking in poor countries
Community	▪ Uses local knowledge of household economic status ▪ Allows communities to define need as they see appropriate ▪ Useful for making sure newly poor are included ▪ Potentially better community buy-in	▪ Risk of elite capture ▪ Community may use different criteria than government or program intends ▪ Concept of community may be difficult in urban areas ▪ Community may wish to avoid dissent or impose social and religious norms ▪ May conflict with primary community role
Self-targeting	▪ Administratively simple ▪ Potentially lower costs ▪ Automatic exit criteria ▪ Has good results internationally for public works or workfare programs ▪ Can maintain work incentives	▪ Historically effective only for public works or workfare programs ▪ Public works programs are not administratively simple ▪ Work requirements and wages are not applicable to many programs ▪ Stigma or time costs may discourage the poor from applying

Source: Adapted in part from Coady, Grosh and Hoddinott (2004)

1.2 Targeting Approaches for Major Social Assistance Programs in Indonesia[16]

Each of the major social assistance programs in Indonesia has used a different mix of targeting methods to determine program beneficiaries, and targeting in practice has often strayed from official guidelines. In this sub-section we review the targeting methods that have been used by BLT, Raskin, Jamkesmas, BSM and PKH. Each program has used a different mix of targeting methods to select beneficiary households and individuals. In addition, targeting in practice has differed from the official guidelines for each program as well, and these differences are summarized.

BLT has used a mixture of community-targeting, self-assessment, and pre-existing lists to collect data, and proxy means testing to select beneficiaries. Table 1.3 summarizes how BLT was targeted in 2005 and 2008, both according to official guidelines and in practice. Key differences include a first stage in 2005 which meant to combine household nominations by sub-village heads with a range of other data, but in practice only households nominated by the sub-village heads were then surveyed with a proxy means test. In addition, after the initial beneficiary lists were announced, protests from many households that had not been included but considered themselves poor led to a second phase of targeting, with households self-selecting themselves to receive the PMT survey conducted by Statistics Indonesia, resulting in a final total of 19.1 million beneficiary households. Most of those surveyed became beneficiaries, as the number surveyed was not much greater than the intended number of beneficiaries, meaning the PMT itself was not the primary selection device in practice. Moreover, the 2008 list largely included the same households as in 2005, for two reasons. First, the 2008 reassessment of households with an improved PMT (PPLS08, discussed later) was not available in time for determining BLT households. Second, and more importantly, community updating of the 2005 list in 2008 failed to remove households who were no longer poor, but only those who had moved or all of whose members had died. Consequently, households who had missed assessment in 2005 were also excluded from the 18.5 million household list of 2008.

BLT was meant to use a mix of data collection methods but in the end relied mainly on sub-village head nominations. Moreover, in 2008 the same list was largely revisited, meaning previously excluded poor households and the newly poor continued to be excluded.

Table 1.3: BLT Targeting in Theory and in Practice

		In Theory	In Practice
BLT 2005-06	Collection	▪ Village head nominates potential poor ▪ Combined with BKKBN[17], regional BPS and local government data	▪ Mostly only village head nominations used ▪ After protests, households could self-apply
BLT 2005-06	Selection	▪ Simplified PMT (no regression scoring)	▪ Mostly as planned, but not all households visited, and not all questions asked ▪ Self-applying households in second stage had same survey but different scoring system
BLT 2008-09	Collection	▪ Used 2005 list as starting point	▪ As planned
BLT 2008-09	Selection	▪ Consultative community meetings update list for households which have moved, died or are no longer poor	▪ Broader community not usually involved in meetings, only village officials ▪ Only households who had moved or all of whose members had died were removed; not removed for being no longer poor ▪ Some informal redistribution of benefits to other households

16 Program targeting approaches are further discussed in World Bank (2012a, 2012d, 2012e, 2012f, 2012g, 2012h and 2012i).

17 National Family Planning Coordination Agency.

Raskin combines geographical targeting to set local quotas, and uses community methods and existing PMT lists of the poor to select beneficiaries. Table 1.4 summarizes how Raskin is targeted according to official guidelines and in practice. As with BLT, the practice often deviates from the theory. The major difference is that instead of using existing lists of the poor as mandated, such as the Statistics Indonesia list used for BLT, or the National Family Planning Coordination Agency (BKKBN) list of the poor, communities can distribute Raskin rice as they see fit. This often means sharing out rice equally amongst all households, poor and non-poor. Frequently the decision as to who is to receive benefits is not made by the community as a whole, but by a local leader. This may involve sharing benefits to avoid conflict and tension.

Raskin is meant to use official lists of the poor to select beneficiaries, but in practice communities distribute the rice as they see fit, often sharing it out amongst many or all households, regardless of economic status.

Table 1.4: Raskin Targeting in Theory and in Practice

	In Theory	In Practice
Collection	▪ Village level quotas set using national PMT-based lists of the poor - BKKBN list before 2006 - BPS list (PSE05) from 2006	▪ BKKBN PMT based only on 5 indicators, not all of which are economic ▪ Neither BKKBN nor PSE05 list uses a sophisticated scoring system
Selection	▪ BKKBN lists of poor used as starting point at village level before 2006 ▪ BPS lists of poor used from 2006 ▪ Consultative community meeting to verify list	▪ Village meetings often not held, or if held, do not include broader community ▪ Lists of poor often not used, at discretion of village head ▪ Sharing out equally among all households very common

Jamkesmas combines geographical targeting to set local quotas, and uses community methods, existing PMT lists of the poor, and self-selection to select beneficiaries. Table 1.5 summarizes the Jamkesmas approaches to targeting. Very much like Raskin, Jamkesmas is meant to apply official lists of the poor to allocate health cards. Again like Raskin, actual practices at the local level vary considerably. Although some districts do use the official lists, in others local health officials, such as village midwives and local health center officials, select beneficiaries themselves, often with their own criteria such as mothers with infants, regardless of economic status.[18] In addition, because of implementation delays in allocating cards in some places, up until recently, letters of the poor were accepted as well. These letters are given by local leaders to households requesting them, effectively making this self-selecting.[19]

Jamkesmas is also meant to use official lists of the poor but experiences considerable variation at local levels, with local health officials sometimes choosing beneficiaries, or households selecting themselves.

Table 1.5: Jamkesmas Targeting in Theory and in Practice

	In Theory	In Practice
Collection	▪ Village level quotas set using national PMT-based lists of the poor - BKKBN list before 2006 - BPS list (PSE05) from 2006 - BPS list (PPLS08) from 2011	▪ BKKBN PMT based only on 5 indicators, not all of which are economic ▪ Neither BKKBN nor PSE05 list uses a sophisticated scoring system ▪ PPLS08 is a sophisticated PMT
Selection	▪ Districts can use BKKBN or BPS lists of poor to allocate health cards	▪ Lists of poor often not used ▪ Village midwives and *puskesmas* officials sometimes determine beneficiaries using own criteria ▪ Not all individuals in households always receive cards ▪ Households can use previous health cards or letters of the poor from the village head to access services

18 See SMERU (2010b).

19 See SMERU (2010a).

The fragmented BSM programs are implemented in different ways. However, typically recipients are nominated by schools and school committees. BSM initiatives typically identify potential scholarship recipients by soliciting nominations from schools and school committees. Students nominated must have already achieved consistent attendance and demonstrated 'good behavior', confirmed by the principal. Recently enrolled students or prospective new entrants have very little chance of being selected; likewise, those who have not made themselves known to the principal are unlikely to be selected. Households cannot nominate their own children and there is currently no formal appeals process. See World Bank (2012h) for further detail.

PKH initially used the 2005 list of the poor developed for BLT, before using an updated 2008 list. When PKH was first piloted in 2007, it used Statistics Indonesia's 2005 list of the poor developed for BLT. Households identified as very poor on this list were eligible.[20] From this set of households, those with pregnant or lactating women, with children 0 to 15 years old, or with children up to 18 years old who had not yet completed 9 years of education, were identified in a supplementary survey.[21] All such households below the cut-off with the right demographic composition were eligible for the PKH program, but the PKH implementing units in Kemensos (UPPKH) chose only some of the eligible households to receive PKH transfers after holding meetings with these households (World Bank 2012i).

1.3 Socialization of Targeted Programs in Indonesia

Public knowledge and understanding of social assistance programs and their targeting is determined by the type and level of information received through program socialization. Public knowledge of social assistance programs depends in large part on the amount and accuracy of information about the program received by all relevant stakeholders and the general public. Early socialization at each stage of the program is important to avoid misperceptions stemming from inadequate or incorrect information. Socialization is also important to prevent program mis-portrayal for political reasons, such as arguing that the program imposes hardships on wider society.

Each stakeholder requires different information, to be socialized through different channels in different forms. As each stakeholder has a different role in a program, different information is needed for their different knowledge requirements. Detailed information on program strategy provides policy makers and politicians clear justifications for whether programs are desirable and should be adequately financed. Potential beneficiaries need to know the program purpose and be aware of their rights and benefits, in order to actively participate, and to ensure their benefits are not diluted. The provision of information should also include the specific responsibilities of local governments, the extent to which local governments can adjust policies to reflect local preferences, and the coordination requirements with central government and implementing agencies. Information campaigns regarding programs must also address the general public. This makes it less likely that they will divert the program benefits to non-target households (intentionally or not), or change local implementation, and allows them to act as a local watchdog on implementation and targeting.

In practice, socialization of social assistance programs in Indonesia has been minimal and unorganized. Socialization activities should be systematically developed and integrated into the overall program design and implementation. However, in the three major social assistance programs studied here, BLT, Jamkesmas and Raskin,[22] official program guidelines only briefly mentioned the information which should be socialized, and who should conduct these activities, without sufficient details on the design of the socialization activities and how they should be conducted at different levels.[23]

Socialization to local governments varies across programs and regions. Distribution of information to implementing agencies is usually conducted through general coordination meetings, instead of specific socialization meetings. However, the level and frequency of meetings varies across programs and regions. Generally the meeting is conducted at the beginning of program implementation, but with different coverage of information, as the generalized program socialization guidelines tend to be very non-specific.[24] In the case of Raskin, Smeru (2008a) found examples

20 By Statistics Indonesia definition a very poor household is a household that has less-than-poverty line expenditure overall; spends a large portion of available income on basic staple food; cannot afford medical treatment (except at the community health clinic or other public health facilities subsidized by the government); and cannot afford sufficient new or replacement clothing. In practice, households meeting these standards have per-capita expenditure levels of approximately 0.8 times the Statistics Indonesia-defined poverty line.

21 This information was collected in the Statistics Indonesia Health and Education Basic Service Survey (*Survei Pelayanan Dasar Kesahatan dan Pendidikan*).

22 Socialization of scholarships for the poor is done mainly by schools, with little being done by the implementing agencies. See World Bank (2012h).

23 SMERU (2006, 2008a, 2009, 2010a)

24 SMERU (2006, 2008a)

where only one sub-district within a district even conducted program socialization. During the 2008 BLT, coordination meetings between different levels of local government and implementing agencies took place after socialization had been implemented due to budget disbursement delays, hampering the communication of consistent and focused messages.[25]

All major programs suffered from inconsistent communication and information being received by communities and beneficiaries.[26] Socialization activities to communities are generally done informally, causing considerable variation in sources of information and inconsistent information being received. Survey data offer an insight into how socialization was done in practice (Box 1.1). Although the village head was usually the primary receiver of information, they often did not pass this directly on to the community. Therefore program beneficiaries generally received information from those distributing benefits, while the broader community heard about the program by word of mouth or from local media. The variation in information source caused further variation in information received. The BLT 2005 and 2008 recipients generally only received information about the program from the village apparatus during the distribution of BLT cards, with limited information regarding venue and schedule of payment.[27] Meanwhile, only half of survey respondents reported receipt of information regarding the program purpose and who should receive the funds. Similarly, socialization about Raskin to the community was meant to cover implementation-related information, such as the quota of rice per household, the price per kilogram, and the collection method. Such information was usually obtained from the people responsible for rice distribution, such as the sub-village head or community figures, but was not consistent, leading to much confusion as to the correct details.[28] In the case of Jamkesmas, the great majority (usually over 80 percent) of beneficiaries either did not know or were misinformed about the program coverage of different inpatient and outpatient services, and information regarding fees and charges for medicines was not well-publicized.[29]

Box 1.1: Survey data offer an insight into how socialization was done in practice at the local level.

Survey assessments of social assistance programs were used to evaluate how program information campaigns were perceived by communities. Survey data used were from the Indonesian Family Life Survey (IFLS) and the evaluation survey of BLT 2005. The IFLS community surveys included two approaches. The first used village-level group discussions, consisting of at least two village officials, and usually including the village head, village secretary, head of village government administration, head of village development, head of village welfare affairs, head of village financial affairs, or head of village general affairs. The second approach interviewed two village informants who were randomly selected from those knowledgeable about government programs in the community, but not involved in village governance. Potential respondents included school principals and teachers, health professionals, religious leaders, youth activists, local political party activists, and local business leaders. The programs covered by these surveys were BLT, Jamkesmas and Raskin. The evaluation survey for the 2005 BLT was conducted in conjunction with the 2006 Susenas. The survey gathered detailed information regarding the program's targeting mechanisms, socialization activities, operational processes, and complaints and grievances from both the recipients and non-recipients of BLT.

In addition to the problems common across all major programs, there were issues specific to each program. Table 1.6 summarizes program specific socialization problems and their effects, showing failures of programs to socialize program objectives, intended beneficiaries, beneficiary rights and benefit amounts, at all levels of government and community.

As with the larger programs, socialization of PKH to affiliated service providers, local governments, and beneficiary households was also generally ineffective. As with most other social assistance initiatives and other government-provided services in Indonesia, socialization and advertising activities for PKH were delegated to the Ministry of Communication and Information (Kemenkominfo). An operations engineering report found that PKH socialization was deficient in content, frequency, and intensity.[30] Spot checks revealed that local governments and service providers as well as local authorities and the community at large did not receive even printed flyers with an explanation of the PKH program.[31] Common sources of program exposure were in sensational media reports of malfeasance by program

25 SMERU (2009).

26 The inadequate socialization will have contributed in part to the public perceptions of the programs and their targeting. These perceptions are explored in Section 3.

27 SMERU (2006, 2009).

28 SMERU (2008a).

29 World Bank (2012g).

30 Ayala (2010).

31 Centre for Health Research (2010).

operators or word of mouth.[32] PKH program officers themselves were sometimes unable to answer simple questions about program goals or eligibility criteria.[33] As it was a delegated function, there was no monitoring of the socialization activities actually carried out and misunderstandings lingered – for example, beneficiaries and PKH facilitators alike were unaware that PKH beneficiaries are eligible for all other social assistance schemes for poor households.[34] Moreover, socialization of the PKH program was deliberately kept to a minimum in order to avoid social jealousy and redistribution of benefits (World Bank 2012i). As a consequence, most beneficiaries rely on PKH facilitators for information on program goals, objectives, conditions, and in general support and encouragement in complying with responsibilities. However, facilitator quality has not been uniform.

All major programs suffered from socialization deficiencies, which have adversely affected targeting outcomes and program satisfaction.

Table 1.6: Socialization Problems and Adverse Effects by Program

BLT Socialization Problems	Raskin Socialization Problems	Jamkesmas Socialization Problems	BSM Socialization Problems
▪ Socialization to community not formal, information obtained via local news, word of mouth, village apparatus ▪ Information not systematic, program objectives, intended beneficiaries and targeting criteria not addressed enough	▪ No specific socialization meetings for implementers ▪ Socialization at district and sub-district level varied by province ▪ No comprehensive program for local socialization, which was informal, only to the community via rice distributors	▪ No comprehensive socialization of program content and included services ▪ No formal planning for socialization of targeting process, while selection varied by district	▪ Guidelines for socialization not developed in operations manuals ▪ No guidelines or explicit funding for outreach activities ▪ No advance socialization to communities before beneficiary selection
Adverse Socialization Effects	**Adverse Socialization Effects**	**Adverse Socialization Effects**	
▪ Half or less of households knew about BLT's objectives, eligibility, and how to complain ▪ Many protests due to lack of socialization of the BLT targeting process and the program's objectives and priorities	▪ Beneficiaries not aware of how much rice they should receive, at what price, and how often ▪ Reduced local government commitment to implementation	▪ Local leaders did not know who target households were ▪ Majority of cardholders do not understand benefits	▪ BSM distributes scholarships to students already exposed to local school system and does not reach out to students with low levels of exposure ▪ Very few school-age children from poor households know about BSM ▪ Beneficiaries and communities not knowledgeable enough to monitor program from the bottom up or participate in either safeguarding or accessing the program

Sources: SMERU (2006, 2008a, 2009, 2010a), Son and Sparrow (2010), World Bank (2012d, 2012h).

32 SMERU (2008c) and Centre for Health Research (2010).

33 SMERU (2008c).

34 World Bank (2012i).

02

Targeting Outcomes in Indonesia

This section examines the current targeting outcomes of social assistance programs, as well as the effectiveness of community-based targeting in Indonesia. In this section we assess current targeting outcomes for the major social assistance programs in Indonesia, before considering how effective community-based targeting methods can be. However, we first discuss how targeting outcomes can be measured, and the difficulties involved.

2.1 Measuring Targeting Outcomes

There are many ways to measure targeting outcomes, but it is difficult to compare outcomes across different programs. There is no single targeting metric used universally in the targeting literature. Common measures include inclusion and exclusion errors (leakage and undercoverage); the proportion of benefits received by target households; the Coady-Grosh-Hoddinott measure (CGH); and less commonly, the Distributional Characteristic. However, no single measure is perfect. In particular, there are difficulties comparing between programs, countries and time periods, particularly when different size programs are involved. The Targeting Metrics technical annex at the end of the report discusses all of the targeting measures in detail, as well as the difficulties in using them to compare targeting outcomes.[35] Boxes 2.1 and 2.2 present two simple examples of how targeting measures can be misleading.

35 See also World Bank (2012c).

Box 2.1: Two programs of different sizes with the same targeting can have different targeting measures

When two social assistance programs are operating at different levels of coverage (or one program at different levels over time), it can be difficult to compare their targeting performance. Targeting metrics can vary by beneficiary levels, even for the same outcomes. We illustrate this by calculating exclusion error (EE, proportion of target households not receiving benefits) at two different levels of random targeting.

First, consider a program covering 10 percent of the population. If randomly targeted, then 10 percent of the poorest 10 percent of the population (the target) will receive benefits, with the other 90 percent missing out (that is, the EE is 90 percent). Next, consider a program covering 30 percent of the population. If randomly targeted, then 30 percent of the poorest 30 percent will receive the program, and only 70 percent of the target population will not, resulting in a 70 percent EE. That is, as program size increases, the EE of a program falls, even if targeting remains random throughout. In a sense, targeting is easier for larger programs, since more of the target population is likely to be included.

Now consider the same two programs with perfect targeting. We can calculate the CGH measure as the proportion of benefits received by the target population divided by the fraction that population is of the whole. So if the target is the poorest 40 percent, and they receive 55 percent of benefits, then CGH = 0.55 / 0.40 = 1.375. For the 10 percent program, the CGH when targeted perfectly is 1.0 / 0.1, or 10. For the 30 percent program, the CGH when targeted perfectly is 1.0 / 0.3 = 3.3. That is, smaller programs have a higher potential CGH score than larger ones.

This report uses two main measures of targeting outcomes. The first are errors of inclusion and exclusion. Inclusion error (IE, or leakage) measures non-poor households who receive program benefits, and is calculated as the proportion of beneficiaries who are not target households. Exclusion error (EE, or under-coverage) measures poor households who do not receive benefits, and is calculated as the proportion of target households who are not beneficiaries. IE and EE are the most commonly used measures, and so are included for reference. However, these measures present a number of problems.[36]

The second targeting performance measure is gain over random targeting. In this report we introduce a new measure in which we compare how well program targeting did compared to if targeting had been random, or not done at all. This measure, gain over random targeting (or *targeting gain*), is a normalization of the popular CGH measure, which compares the proportion of benefits received by a target population to the size of the target population.[37] We adapt this measure, but transform it so that it is a number between 0 and 100, where 0 represents the same outcome as if targeting had been random, and 100 represents perfect targeting, or the result if all the benefits had been received by the target population. That is, the *targeting gain* represents how much better than random a program's outcomes were, relative to perfect targeting.[38] The new measure is both more intuitive to interpret and more consistent to compare across programs and periods.[39]

These measures are calculated at different levels to better understand the type of targeting errors that programs are making. A wealthy household far above the program threshold (say, the poorest 30 percent) receiving a program may be considered a worse error than a non-poor household just above the threshold. Similarly, a very poor household far below the threshold who misses out on the program may be considered a worse error than a poor household close to the threshold. To account for this, we calculate our two measures at different levels. For example, we calculate three exclusion errors, increasingly defining the target population as those below the official very poor line, the official national poverty line, and the official near-poor line, as defined by Statistics Indonesia.[40] All are target households for the main programs, but we might hope that the EE is lower when we consider just the very poor rather than up to the near-poor and below. Similarly, we calculate our targeting gain for different levels of the target population, beginning with the official target – those beneath 1.2x the poverty line – but expand it to include those beneath 1.4x, 1.6x, 1.8x and 2x. When calculated at a higher poverty line, say 1.4x, non-poor households just above 1.2x the poverty line are no longer counted as targeting errors, and our targeting gain increases. Good targeting outcomes should see targeting gains increase significantly as they are calculated for higher poverty lines, indicating that the targeting errors at the official target level are less serious.

36 See Boxes 2.1 and 2.2.

37 See the Targeting Metrics Technical Annex for a more technical discussion.

38 The targeting gain is calculated by: $gain = \frac{CGH(X) - CGH(X)_{random}}{(X)_{perfect} \quad CGH \; X \;\; _{random}} = \frac{CGH(X) - 1}{CGH \; X \;\; _{perfect} \quad 1}$, where CGH(X) is the CGH measure for the program, CGH(X)random is the CGH measure for random targeting, and CGH(X)perfect is the CGH measure for perfect targeting, all calculated at level (X), the percentage of the total population covered by the program.

39 The maximum CGH score a program can receive depends on the size of the target population (see Box 2.1). Comparing scores of programs with different coverage levels is thus difficult to do meaningfully. Normalizing the score relative to the maximum possible (perfect targeting) makes individual scores easier to interpret and comparisons across periods or between programs more appropriate.

40 The very poor are those beneath approximately 0.8x the poverty line, the poor are beneath 1.0x the poverty line, and the near-poor are beneath 1.2x the poverty line.

Box 2.2: Targeting measures can also be misleading when the number of beneficiaries a program has is different from the number of households it officially targets

In Box 2.1, we treated the number of beneficiaries and target population as equal in size, but often this is not the case. That is, the proportion of the population covered by a program may be more or less than the proportion of the population targeted by a program. We look at two examples here where beneficiary and target levels vary, and the implications for targeting metrics.

First, it is quite common for government programs to lack to resources necessary to accommodate all intended beneficiaries. Consider a program targeted at the poorest 30 percent, but with a budget for only 10 percent. Even if targeting is perfect and the poorest 10 percent of households receive the program, two-thirds of the targeted beneficiaries are not covered, giving an EE of 67 percent. So despite perfect targeting, the program would result in targeting errors for non-targeting reasons.

Next we consider a contrasting situation, where the beneficiary level is greater than the target level. Such a situation can occur, for example, when local governments use their own budgets to augment federal programs. This can also create different problems for targeting metrics. Consider a program where the target level is the poorest 30 percent, but funding is sufficient for 40 percent. Even with perfect targeting, where the poorest 40 percent receive the program, the IE calculated at target levels is 25 percent, as non-target households necessarily represent a quarter of beneficiaries, given that all target households already receive the program.

Thus IE and EE are sensitive not only to differing beneficiary levels between programs, but also to differences in a program's beneficiary levels and its target levels. When beneficiary and target levels are the same, IE and EE have the same value – for one non-target person to receive the program, one target person must miss out. But when beneficiary and target levels are different, IE and EE are different. When beneficiary levels are below target levels, EE is higher than IE (target people can miss out even when non-target people are not included), and when beneficiary levels are above target levels, IE is higher than EE (non-target people can be included even when target people are not excluded).

2.2 Current Targeting Outcomes for Social Assistance Programs in Indonesia

In Indonesia, despite most major social programs having the same target population, actual beneficiary levels vary by program. Beneficiary levels vary by major program, despite most having the same target population.[41] With the official near-poor rate having fallen since program targets were established, all programs have coverage rates above the current near-poor rate. Total BLT and Jamkesmas recipients are similar to the number of near-poor, but Raskin is received by far more households than intended (Figure 2.1). The official target population is households with a per capita consumption below around Rp 250,000 per person per day; this represented 12.1 million households in 2010, or 21 percent of all households,[42] but was closer to 27 percent when BLT was initiated in 2005. While 27 percent of households did in fact receive BLT in 2008-09,[43] nearly 50 percent bought rice under Raskin. As discussed, Raskin beneficiary levels were greater than intended, and come at the cost of recipient households receiving considerably less than the intended monthly quota.[44] Two estimates are presented for Jamkesmas, the first being card *holders* (30 percent of households reported having a card in 2010), the second being card *users* (11 percent reported using a card to receive free health care).

41 BSM covers only 3 percent of students aged 6 to 18 years.

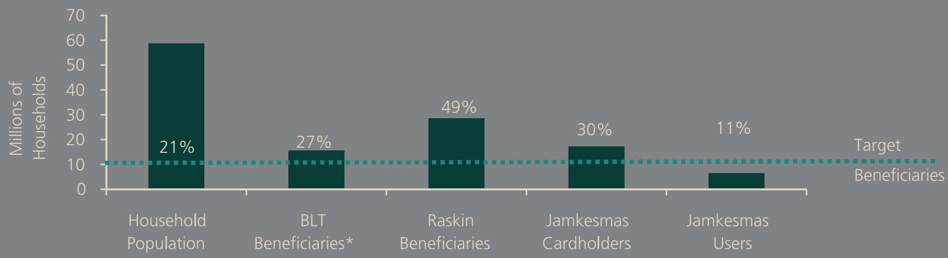
42 Calculated from Susenas.

43 Household survey weights are used, based on Statistics Indonesia population projections, and thus total coverage varies from official data (19.2 m). This holds for all programs discussed in this section.

44 See World Bank (2012f).

The actual numbers of Jamkesmas and BLT beneficiaries are only slightly higher than target levels, but Raskin is twice as high due to redistribution of rice.

Figure 2.1: Program Beneficiary Levels, 2010



Source: Susenas
Notes: Number of households is sum of survey weights and differs from administrative data, but is consistent with the survey number of poor and near poor. Percentages above bars are number of beneficiaries as a percentage of all households in Indonesia. BLT beneficiaries are for the 2008-09 program.

Three major current programs are pro-poor in their targeting, but still suffer from deficiencies, with many of the poor excluded and many non-poor included. Figure 2.2 shows the percentage receiving each program in 2010 (2009 for BLT) with the population grouped into ten equal groups from poorest (decile 1) to richest (decile 10).[45] While Raskin is received by 71 percent of the poorest three deciles, 52 percent of the next four deciles also participate, and even 23 percent of the second richest decile, leading to nearly 70 percent of all beneficiaries being non-poor (see inclusion error, Figure 2.4), and receiving well over half of all program benefits (Figure 2.3). BLT's coverage of the poorest three deciles is 46 percent, lower than Raskin, but it was also only received by 18 percent of non-target households,[46] with much fewer included from the richest 20 percent (Figure 2.2), resulting in lower inclusion and higher exclusion errors (Figure 2.4), and a higher percentage of total benefits being received by target households (Figure 2.3). Jamkesmas has a similar result to BLT, with similar coverage of the poorest three deciles (45 percent), but higher coverage of non-target deciles (23 percent). The usage percentage of Jamkesmas is relatively constant across deciles, with about one in three cardholders reporting using free health services in the last six months at each decile.

Current programs are pro-poor, with poor households being more likely to receive benefits… …but a considerable proportion of total benefits going to non-poor households.

Figure 2.2: Percentage Receiving Programs by Consumption Decile in 2010

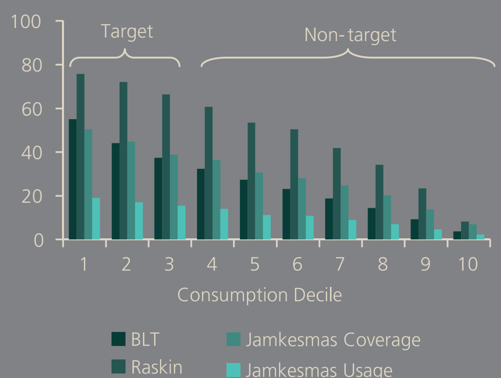
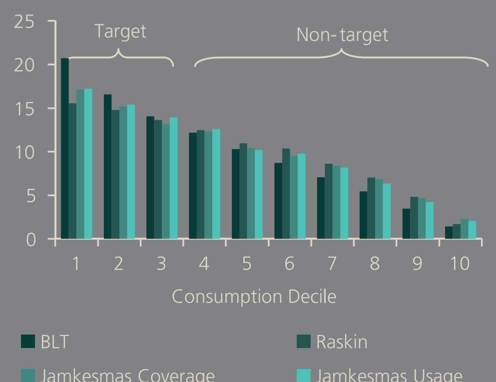


Figure 2.3: Percentage of Total Benefits Received by Consumption Decile in 2010



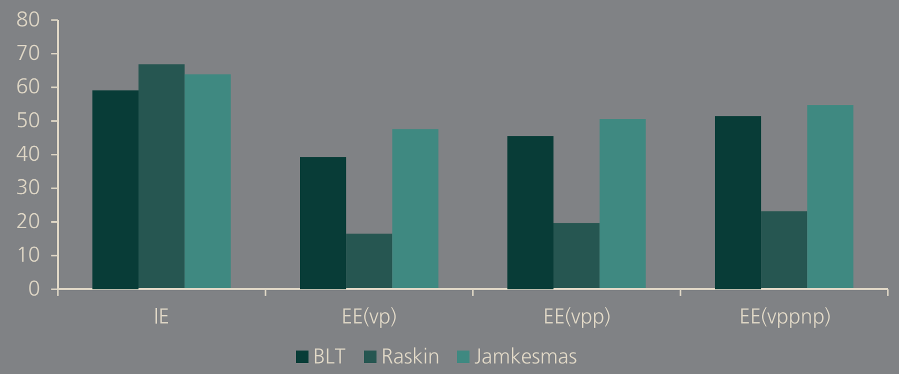
Sources: Susenas and World Bank calculations.
Notes: BLT results are for 2009.

45 Deciles are based on per capita consumption, adjusted for spatial poverty basket pricing differentials.

46 Full data including a breakdown of each program by sub-group are contained in the Data Annex.

Many poor households are excluded and many non-poor receive program benefits.

Figure 2.4: Inclusion and Exclusion Errors by Program (Percentage)



Sources: Susenas and World Bank calculations.
Notes: All data are for 2009. IE is exclusion error, calculated at target levels. EE is exclusion error, calculated for very poor (vp), poor and below (vpp) and near-poor and below (vppnp), according to official Statistics Indonesia definitions.

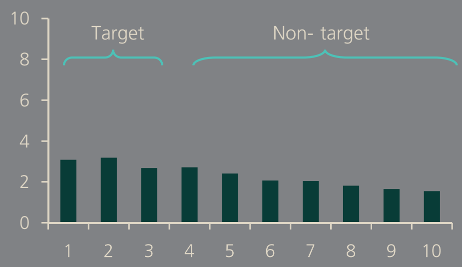
However, BSM is nearly equally likely to be received by non-poor households as the poor. Students from the poorest 40 percent of households account for approximately half of all BSM scholarships (and half of all BSM transfers) while households in the top 60 percent by consumption receive the other half of scholarships (Figure 2.6). That is, a BSM transfer is nearly as likely to be received by a student from a poor or vulnerable household as by a student in a richer household (Figure 2.5). BSM also systematically discriminates against new or prospective students. Potential scholarship recipients are nominated by schools and school committees. Students nominated must have already achieved consistent attendance and demonstrated 'good behavior' confirmed by the principal. Recently enrolled students or prospective new entrants have very little chance of being selected; likewise, those who have not made themselves known to the principal are unlikely to be selected. (See World Bank 2012h). Moreover, children in poor households who are not in school, perhaps the most deserving of potential students, are not considered at all.

Sufficient data are not yet available to assess PKH targeting properly. However, there is evidence that the households selected into PKH are more disadvantaged than eligible households who were not. Susenas did not ask about PKH beneficiaries before 2010, and the small scale of the program means that there are not sufficient data in the subsequent Susenas to properly evaluate targeting outcomes. However, data from the PKH impact evaluation report (World Bank 2010c) can be used to examine households from the list of very poor and demographically eligible households from Statistics Indonesia, some of whom received PKH and some of whom did not (see also World Bank 2012i). Since not all very poor households could be covered by PKH, Kemensos, the implementing agency, selected households from the Statistics Indonesia eligible list. The impact evaluation survey of eligible households indicates that the two sets of households – eligible but not chosen to receive PKH, and PKH recipients – are significantly different based on observable characteristics. Generally, PKH households are younger, with more members, more often female-headed, more often working in agriculture, less educated, with fewer assets, more often recipients of other social assistance programs like BLT and Jamkesmas, and with lower levels of monthly per-capita expenditure. All of this implies that households selected to be PKH recipients are poorer, larger and less well-educated and more often exhibit characteristics that are non-income correlates of poverty. Moreover, eligible households, whether selected for PKH or not, had an average monthly per-capita household expenditure of around Rp 190,000, malnutrition (under-weight-for-age) rates of 23 percent for 0 to 3 year olds, and primary education or lower for household heads 85 percent of the time. That is, Statistics Indonesia has identified very poor households on average.[47]

47 What is not known is how many very poor households were excluded from this list, and whether they were poorer than actual beneficiaries.

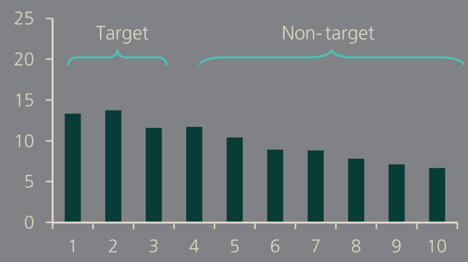
Students from households of any consumption status are nearly as likely to receive BSM as any other…
…with a large proportion of total benefits going to non-poor households.

Figure 2.5: Percentage of 6-18 Year Olds Receiving BSM by Consumption Decile in 2009



Sources: Susenas and World Bank calculations.

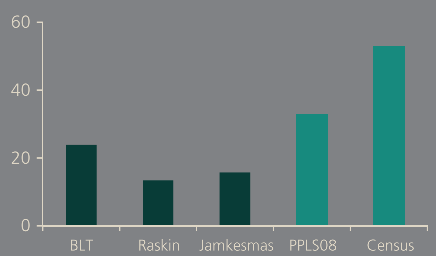
Figure 2.6: Percentage of Total Scholarships Received by Consumption Decile in 2009



BLT has the most accurate targeting of the major programs. However, there remains significant room for improvement, with current Indonesian targeting outcomes falling well short of benchmark outcomes if all households were to be surveyed. Figure 2.7 compares the gains over random targeting for each of three programs in 2010. BLT performs the best, with targeting gains of 24 percent. That is, targeting outcomes under BLT are 24 percent better than if the same number of benefits had been distributed randomly, out of a maximum of 100 percent if all the benefits had been received by the near-poor and below (the target households). Jamkesmas and Raskin had targeting gains of 16 and 13 percent each. Two benchmarks are also included in Figure 2.7. 'PPLS08' represents an estimate of targeting the near-poor and below using the list of the poor developed by Statistics Indonesia in 2008 but not yet used to target a major social assistance program (see Box 4.1). The improved PMT used in 2008 would have led to targeting gains of 33 percent, a significant increase on the best-performing program, BLT. The 'Census' result in Figure 2.7 represents an 'ideal' benchmark, where all households are surveyed with the 2008 improved PMT (rather than the 2008 subset of households visited). This approach results in a targeting gain of 53 percent, and although it might not be implemented for financial or practical considerations, it is quite feasible and thus represents a benchmark against which program targeting should be compared.

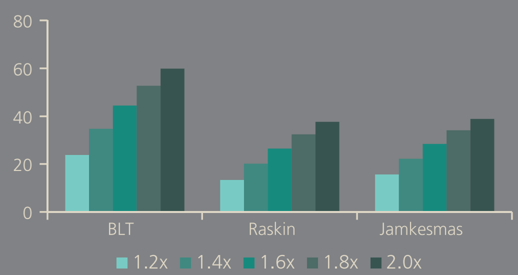
BLT is the most accurate program with the highest targeting gain…
…but there remains significant room for improvement, with many of the benefits going to households far from the program eligibility threshold.

Figure 2.7: Targeting Gains by Program and Benchmarks, 2010



Sources: Susenas and World Bank calculations.

Figure 2.8: Targeting Gains at Different Target Levels by Program, 2010



Sources: Susenas and World Bank calculations.

Notes: BLT data are for 2009. Near-poor level of 1.2x poverty line is target coverage level for all programs. Targeting gains are based on the CGH targeting measure, subtracting CGH for random targeting and normalizing by CGH for perfect targeting less CGH for random targeting. Gains are relative to random targeting at program target levels and range from 0 percent (random or no targeting) to 100 percent (perfect targeting – target households receive 100 percent of benefits). PPLS08 was simulated by applying PPLS08 PMT specification to BLT households and re-ranking. Census means applying PPLS08 PMT to all households and ranking.

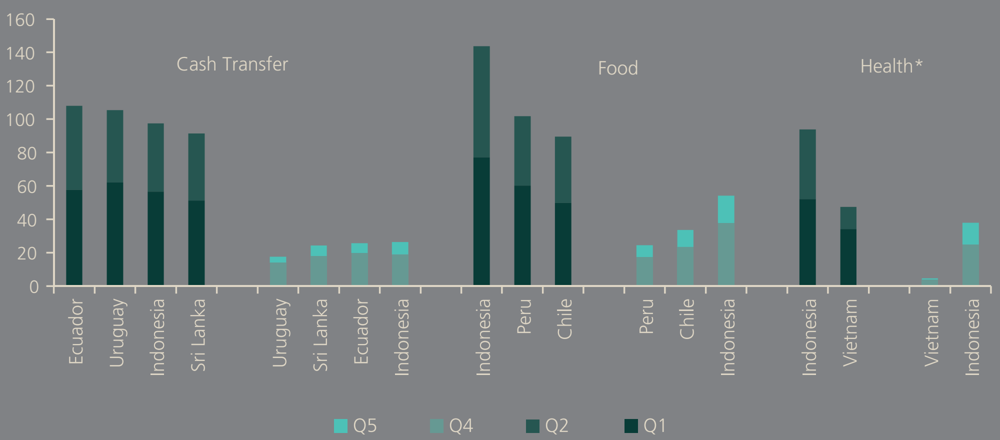
Potential improvements are also evident when considering the distribution of beneficiaries, with many of the benefits going to households with much higher consumption than the program thresholds. The targeting gains for each program are still relatively low, even for the best, BLT. In Figure 2.8 we calculate the targeting gains for an expanded definition of the target population. That is, we let households who are just above the target threshold count as target households. Thus, if the program benefits not going to target households are going to those who are near-target, these secondary targeting gains should increase steeply. If they remain relatively flat, then most of the non-poor who benefit are far from the program threshold. When we allow households below 1.4x the poverty line and 1.6x the poverty line to also count as correct targeting, the targeting gains for BLT increase from 24 percent to 35 and 44 percent respectively, which indicates that a significant proportion of benefits received by the non-poor go to households with consumption that is still relatively low. Raskin targeting gains increase from 13 percent to 20 and 27 percent, indicating that some program inclusion error is related to households which are close to the target threshold. Similarly, Jamkesmas gains increase from 16 percent to 22 and 28 percent, suggesting that many incorrectly included non-poor households are not that poor. Even when we calculate the gains for households beneath 2x the poverty line, they increase to only 60 percent for BLT and less than 50 percent for the other two programs, indicating that a substantial proportion of benefits goes to households which are far above the program threshold.

Comparing targeting outcomes across different programs and countries is very difficult. As discussed previously, there is no single measure that is suitable for making international comparisons of targeting performance. Targeting measures are very sensitive to how they are calculated, and even when calculated in the same way, they can give different results depending on the coverage of the program and the proportion of the population being targeted. Moreover, even apparently similar programs may vary substantially in their design and implementation. The targeting environment also differs by country, with Indonesia having one of the most difficult (see introduction to this report). Nonetheless, with these strong caveats in mind, some international benchmarks can be examined to illustrate the level of improvement in targeting Indonesia might aim for. The overseas programs included here are of similar scale to each of their Indonesian counterparts (thus excluding the well-known but smaller Brazilian and Mexican programs), and have been selected as among the better targeted programs of their kind.[48]

Indonesian program coverage of the poor is in line with international comparisons, but leakage to the richest is higher than well-targeted programs overseas. Figure 2.9 compares Indonesian program coverage to well-targeted programs of a similar type from other countries. Coverage comparisons are shown for the poorest 20 percent of the population (quintile 1, Q1), next poorest 20 percent (Q2), up to the richest 20 percent of the population (Q5). Considering coverage of Q1 and Q2, BLT is not far from the better targeted cash transfer programs. Good international comparisons for in-kind food and health programs are difficult to find, but both Raskin and Jamkesmas have greater coverage of the poor than international comparisons, although they both have nearly twice as high total coverage of the population as the comparisons, and in Raskin's case this results in benefit dilution and redistribution. However, for all programs, Indonesia covers more of Q4 and Q5 than international benchmarks, indicating costly program leakage to the least deserving households.

Indonesian program coverage of the poorest is relatively good compared to international benchmarks, although there is room for improvement. However, it experiences higher leakage to the richest than well-targeted programs in other countries…

Figure 2.9: International Comparison of Program Coverage of Population by Economic Status (Percent of Quintile Receiving Program)



Source: Social Protection Atlas (World Bank), from Social Protection module of ADePT.
Notes: Cash transfer programs vary in type. Sri Lanka, Ecuador and Indonesia are unconditional cash transfers or last resort programs, Uruguay is an "other cash transfer" program, such as family, child or disability allowance. "Q1" is the poorest 20 percent of the population, "Q2" is the second poorest 20 percent of the population, and so on until "Q5", which is the richest 20 percent of the population. ADePT groups social security and health insurance programs together.

48 Complete data are available in the Data Annex, so the interested reader can make their own comparisons.

Relatively high coverage of non-poor households means that the percentage of benefits enjoyed by the poorest 40 percent lags behind international benchmarks, while the percentage enjoyed by the richest 20 percent is higher than in other countries. When the percentage of total Indonesian program benefits received by Q1 and Q2 is compared to well-targeted programs in other countries, Indonesian outcomes lag other programs (Figure 2.10). Furthermore, the percentage received by Q5 is considerably higher than most international best outcomes.

…meaning the percentage of benefits received by the poorest people in Indonesia lags behind international benchmarks, while the richest households enjoy a higher percentage of benefits than in other countries.

Figure 2.10: International Comparison of Program Benefit Incidence by Economic Status (Percent of Total Benefits Received by Household Consumption Quintile)

Source: Social Protection Atlas (World Bank), from Social Protection module of ADePT.
Notes: Cash transfer programs vary in type. Sri Lanka, Ecuador and Indonesia are unconditional cash transfers or last resort programs, Uruguay is an "other cash transfer" program, such as family, child or disability allowance. "Q1" is the poorest 20 percent of the population, "Q2" is the second poorest 20 percent of the population, and so on until "Q5", which is the richest 20 percent of the population. ADePT groups social security and health insurance programs together.

Performance also varies across provinces and districts. Targeting performance varies across regions. We can calculate targeting gains at provincial and district level. Figure 2.11 presents 2009 BLT targeting gains by province as an example. Much of Sumatra and Kalimantan have the worst targeting performances, while Eastern Indonesia generally performs better. Further research is needed to understand why these differences exist, in order to improve targeting outcomes in all of Indonesia. Possible reasons include the greater difficulty of targeting in urban areas, differing quality of program socialization (informing implementers and communities of the intended beneficiaries and proper targeting methods, and beneficiaries of their rights), local government supervision of targeting, and differing local norms of conflict avoidance or sharing. In the case of Sumatra, this may also have been due in part to many non-poor households receiving benefits because of an over-quota program, which we discuss next.

Targeting performance also varies by province…

Figure 2.11: Targeting Gains for BLT by Province, 2009

Source: Susenas and World Bank calculations

Some areas have more beneficiaries than poor households, and others less. In addition to variable targeting performance, there are also variable relative levels of beneficiaries across regions. We can compare district and provincial estimates of the number of near poor households from the national socio-economic survey (Susenas) to the number of program beneficiaries reported in the same survey. The difference between these represents an area's degree of under- or over-quota, which we can express as a percentage of the number of near-poor. BLT, for example, underserved Java and parts of Sumatra and Sulawesi, and over served Kalimantan and most of Eastern Indonesia, relative to their poverty rates (Figure 2.12). Thus there is a need to make program quotas consistent with district level poverty rates.

…due in part to some provinces having too many beneficiaries relative to the poor population, while other provinces have too few.

Figure 2.12: BLT Under- and Over-quota Rates by Province, 2009

Source: Susenas and World Bank calculations

Female-headed households are considerably more likely to receive each of the programs, regardless of consumption levels, but there is no difference in male and female targeting outcomes at an individual level, and only somewhat of a rural advantage over urban areas. We also examined differences in targeting outcomes amongst different groups. While the total number of poor male and female individuals who benefit or are excluded from programs is almost identical for all programs, female-headed households are far more likely to receive each program than male-headed households of the same consumption level.[49] In other words, when we count all *individuals* living in beneficiary households, males and females benefit equally at all economic levels. However, when we count all *households* receiving benefits and consider the sex of the head of household, poor and non-poor female-headed households are more likely to be beneficiaries than their male-headed counterparts. Poor rural households are moderately more likely to receive assistance than poor urban ones, which reflects the difficulty of targeting in urban areas, and possibly also a tendency to be over-quota in rural areas and under-quota in urban ones.

Different targeting approaches mean different beneficiaries for each program, even though they all target the same households. As we have seen, each of the programs approaches targeting in a different way and has a different database of beneficiaries. As a consequence, even though all three programs target the same target population (the near-poor, or bottom 25 to 30 percent of households), less than one third of target households receive all three programs, while nearly half receive one or no program (Table 2.1). At the same time, over 10 percent of non-target households receive all three, including many of those in the richest half of the distribution.

Less than one third of poor and near-poor households receive all three programs, while at the same time more than 10 percent of the non-poor do, including those in the top half of consumption.

Table 2.1: Number of Programs Received by Households by Poverty Category, 2009

Programs Received	Percentage of Each Poverty Classification by Number of Programs Received								
	Very poor	Poor	Near-poor	All poor	25-50th percentile	51-80th percentile	81-100th percentile	Non-poor	Total
0	9	14	19	16	28	51	81	49	41
1	24	27	31	28	33	27	12	26	26
2	28	25	23	24	20	13	4	13	16
3	39	34	27	31	19	10	2	12	16
Total	100	100	100	100	100	100	100	100	100

Sources: Susenas and World Bank calculations.

2.3 The Role of Indonesian Communities in Targeting

This section concludes by examining the targeting effectiveness of community-based methods. In addition to the targeting outcomes of current social assistance programs, we also review the evidence on the effectiveness of community-based targeting as a method in Indonesia. First, the strengths and weaknesses of community targeting are considered, before its effectiveness in the field is examined.

Community Targeting, Strengths and Weaknesses[50]

Community-based targeting relies on local knowledge to identify the poor and vulnerable, but can take many forms. Community-based methods mean the community input helps determine who potential program beneficiaries should be. This could involve the entire community, a representative subset, or just certain elements, such as community leaders. Selection of beneficiaries may be transparent and consultative or opaque and unilateral, with a structured or unstructured process, and pre-defined or arbitrary criteria.

Community-based targeting has various potential strengths. Local actors may have better information on local poverty conditions than a centralized agency, with lower costs of verification and possibly collection. Moreover, local knowledge can account for recent changes in or shocks to household welfare. Community-based methods can allow the community to define poverty as they see as appropriate. This allows for flexibility for different indicators to be considered in different communities when relevant. Community involvement may also increase satisfaction with targeting outcomes in two ways. First, final beneficiary lists may be closer to community opinions due to their influence on the process, so they may consider the outcomes 'more accurate'. Second, the act itself of having been part of the process may make

49 See Data Annex for results by program.

50 This part of the report draws heavily from Coady, Grosh and Hoddinott (2004).

local households feel more consulted, and this may increase their satisfaction, even if they do not fully agree with the final outcome. Increased community satisfaction will strengthen their buy-in of the targeting outcomes, and thus make them more likely to implement the official targeting intentions without informal substitution of beneficiaries or sharing of benefits.

This approach to targeting also has potential weaknesses. The elite capture of the targeting process and outcomes is a possibility. When targeting is left to the community, the possibility exists for corruption, nepotism or political exploitation. For example, when a community leader alone determines the beneficiaries, he (and it is usually a he) might include relatives and friends on the list, even when they clearly are not deserving, or he might include or exclude certain households for political advantage. Similar risks exist when decisions are made by small meetings of local elites. Even when the broader community is involved, it is possible that local elites and leaders may capture the process and shape the outcomes in a fashion unintended by implementing agencies. Finally, even when motives are clean, there may be a potential conflict with a community leader's primary community function, such as a teacher who selects scholarship recipients but must also maintain general parent trust. In addition, the considerations used by communities and the accuracy of their assessments of household poverty are not well-known. It is generally unclear what information communities use to identify program recipients. Furthermore, the criteria to which this information is applied can also be uncertain. This also means that local communities may select beneficiaries according to criteria that differ from program and government objectives and targets. Finally, the nature of communities can also be a challenge for community targeting. Some communities may wish to avoid dissent or conflict and decide to allocate benefits equally. Others may share benefits due to a strong culture of community sharing, or a general disagreement with the concept of targeting. More generally, defining a community can be difficult, especially in urban areas. It is also unclear whether urban communities actually have sufficient knowledge about all of their members.

There is clear interest in Indonesia from local governments in using community targeting. A community targeting initiative was implemented in 2008 in the district of Polewali Mandar, as discussed in Box 2.3. The outcome of this process has been used by the local government to target various local programs, and has since been adopted by a number of other districts in Sulawesi. This suggests demand by local actors (governments and communities) for community involvement in targeting of social assistance programs.

Box 2.3: Community Targeting in Polewali Mandar District.

In the district of Polewali Mandar in 2005, as in other districts, some poor households were excluded from the Raskin or BLT beneficiary lists while some non-poor households were not. In response, a team from SOfEI, UNICEF Makassar and the Polewali Mandar local government decided to conduct an independent update of the poverty status of all households in the district. Believing that errors in the existing beneficiary lists were partly due to a lack of community involvement, the updating process included the community at every step of the activity, called PDKBM (*Pemutakhiran Data Kemiskinan Berbasis Masyarakat* – Community Based Updating of Poverty Data).

Focus group discussions were conducted at the village level to identify poverty indicators meeting local criteria. The suggested indicators were further discussed and finalized at district workshops, involving various local government offices, such as development and planning, statistics and sectoral (education and health) offices, as well as local NGOs. The required data were collected through a complete survey (census) of all households in the area. A simple PMT scoring system was then applied to the collected data to categorize households as poor and non-poor. Initial results were then presented to communities to verify, through community meetings. Communities could change the lists, by adding or removing households, based on the information they thought most relevant and current. This process was often long and intense, but attracted enthusiastic and substantial participation.

The final list of the poor resulting from the community verification has been better accepted by the communities and is regarded by them as the most accurate poverty data for the area. The inclusion of the community in the PDKBM process has in turn developed greater trust in the local government by the community, trust among community members themselves, and encouraged openness and honesty socio-economic conditions. The local government has decided to use the PDKBM data for several local poverty programs, such as additional quotas for Raskin, scholarships and the mapping of sub-district development programs. PDKBM has since been replicated in other districts in South Sulawesi and West Sulawesi.

Evaluating Community Targeting in Indonesia

There is a substantial history of community involvement in targeting in Indonesia. Indonesian communities have long been involved to some extent in the targeting and selection of household and individual beneficiaries for certain safety net programs. As discussed in Section 1, sub-village heads nominated potentially poor households to be surveyed by Statistics Indonesia for the 2005 BLT; communities often informally redistribute Raskin rice as they think most appropriate; and local health officials and midwives sometimes allocate health cards according to their own criteria.

However, the community-based approach has not always improved results. Section 2.2 has examined current targeting outcomes, finding them pro-poor but with substantial improvement possible. The role that communities have been allowed, and not allowed, to play in current targeting has contributed to this result. Instead of a carefully structured process for community involvement with standardized training and implementation and checks and controls, communities (or elements of) have had wide discretion to determine outcomes, with little education on intended beneficiaries or selection methods, meaning they often do not know who to target, or are not willing to target. The total discretion of community leaders or the broader community over distributing Raskin has been a main cause of benefit dilution for poor households in many villages, and the majority of the rice goes to the non-poor. In contrast, excluding the broader community was a contributing factor to sub-optimal targeting outcomes for both BLT and Jamkesmas. If more than just the sub-village head had given input on potentially poor households to be surveyed for BLT, then the final exclusion error of over 50 percent of target households may well have been lower. Similarly, having only local health officials determine which households receive Jamkesmas cards has meant the use of non-poverty criteria in some areas to identify what should have been poor households.

Statistics Indonesia, the World Bank and J-PAL conducted a field pilot to examine how different methods including community targeting could be applied effectively in Indonesia. In 2008 and 2009, Statistics Indonesia, the World Bank, and J-PAL Poverty Action Lab at MIT conducted a randomized field experiment in 640 Indonesian villages comparing the effectiveness of the different methods at identifying poor households and subsequent community satisfaction with the process and results of different targeting methods. In particular, they compared PMT to community selection. The results from this first targeting experiment are summarized through the rest of this section.[51] A description of each approach is in Box 2.4.

Box 2.4: A field experiment compared a proxy means test to a community-based approach to targeting

To determine beneficiaries using a proxy means test, the experiment surveyed all households in a treatment area, collecting 49 different indicators, including housing characteristics, assets, household composition, head of household education and occupation, and village characteristics. Scoring weights were derived from existing socio-economic surveys, and PMT estimates of household per capita calculated. Those households with scores below a specific cut-off received the cash transfer.

In villages which used the community-based method, the community ranked all households in a sub-village from poorest to richest. The poorest up to a preset quota received the cash transfer. The experiment facilitator had the community make pairwise household comparisons to produce a complete rank-list. Different types of community meetings were held to see how different outcomes would be. Half of the communities held a full community meeting, where everyone was invited and an effort was made to have a broad representation of members attend, while in the other half of communities, only a small number of community elites met to do the rankings. Half of the meetings were held during the day, and half at night, in order that women and men, respectively, were more likely to attend.

Proxy means testing had the lowest rate of mistargeting overall, but communities were better at identifying the very poor. Aiming to identify the poorest 30 percent of households, mistargeting by PMT was 30 percent across all households,[52] compared to 33 percent for community-based methods. Overall, targeting outcomes for both methods were similar to that of BLT discussed in Section 2, and do not in themselves represent a methodological improvement. However, communities were better at identifying the very poor, correctly categorizing 67 percent of the very poor (bottom 10 percent) as poor, compared to 56 percent by PMT (Figure 2.13), and it is in this area that community-based methods may lead to improved targeting outcomes.

51 See Alatas et al. (2010) for a full report.

52 Counting a poor household excluded or a non-poor household included as mistargeting.

Community-based targeting outcomes did not vary when the meetings had different gender mixes. Half of community meetings were held at night, and the other half in the day. Day meetings had a greater proportion of females attending (49 percent) than evenings meetings (39 percent). Nonetheless, there was no significant difference in targeting outcomes between the two different meeting times.

Proxy means tests resulted in lower mistargeting over all households, but rankings by the community identified more very poor households… ……and communities were more satisfied with the outcomes and process when they had been involved in the selection, compared to PMT.

Figure 2.13: Percentage of Household Consumption Deciles Identified as Poorest 30 Percent by Different Targeting Methods

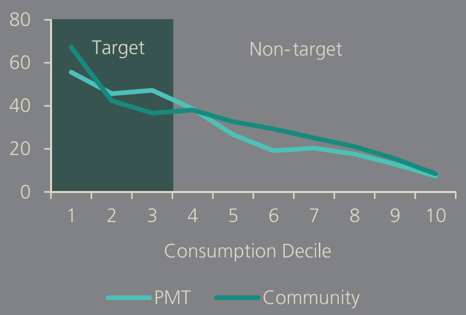
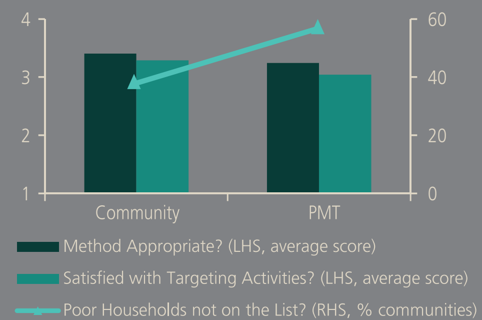


Figure 2.14: Satisfaction Outcomes for Community and Proxy Means Testing



Sources: Targeting experiment, World Bank calculations. See Alatas et al. (2010).
Notes: Respondents were asked to rate the appropriateness of the targeting method used, from 1 to 4, higher being better. Similarly, they were asked how satisfied they were with the targeting activities (1-4), and whether there were any poor households which were not on the list (yes/no).

Community mistargeting increases as the process becomes lengthy; restricting the number of households to rank may improve its effectiveness. When mistargeting rates for households ranked early in the process were compared to those ranked towards the end, there were sharp differences. The first household was 6 percentage points less likely to be mistargeted than the last one. Overall, the community treatment targets slightly better than the PMT in the beginning, but substantially worse towards the end. That is, fatigue was a major weakness for the community methods, suggesting that selecting a smaller number of households will improve community targeting effectiveness.

Initial observations of a second field test suggest that PMT-community hybrids can identify poor households excluded by PMT lists alone. A second experiment has recently been fielded (see Box 2.5). One method explored in this experiment was a hybrid PMT-community approach in which a pre-existing PMT list of prospective beneficiaries was put in front of the community, and they were able to add additional poor households not on the list, up to a set quota, and in some cases, switch out households on the list for ones not on the list. Results are still being evaluated,[53] but initial observations of the pilot stage suggest such a hybrid can be more effective than pre-existing PMT lists alone. Many of the households added by the community were not on the PMT list of the poor, which has previously been estimated to exclude around half of all poor households. While evaluation of these new households' poverty status is still underway, initial results suggest that they are on average 6 percent poorer than households on the PMT list (Box 2.5).

Moreover, satisfaction with the targeting process is much higher for community targeting. As well as targeting accuracy, it is important that local communities and governments are satisfied with targeting processes and outcomes, in order to ensure their buy-in. When communities are unhappy with the process or outcomes (or do not understand the targeting objectives), they may redistribute benefits, undermining program effectiveness. We have previously discussed the prevalence of this in Raskin and Jamkesmas.[54] Conversely, when they understand the objectives and perceive identified beneficiaries as deserving, then they will be more likely to implement official targeting lists. In the experiment, community-based targeting villages were more satisfied with targeting activities compared to PMT villages, they felt that fewer households had been wrongly excluded from or included on beneficiary lists, and they made fewer complaints (Figure 2.14).

53 A full report will be available in 2012.

54 There is evidence of increasing redistribution of BLT benefits during the 2008-09 program, relative to the 2005-06 program, as discussed in World Bank (2012d).

Box 2.5: A field experiment compared a proxy means test to a community-based approach to targeting

In 2010 and 2011, Statistics Indonesia, the World Bank, and J-PAL conducted a second field experiment to examine both the feasibility and effectiveness of community verification and self-targeting methods when used with Indonesia's conditional cash transfer program PKH.

In the 200 villages that used the community verification method, facilitators invited community members to a meeting to determine the CCT recipient list. Meeting attendees verified that the poorest households by 2008 PPLS08 PMT score still lived in the area and had children in school. Participants were then asked if they would like to add households to the list. In half of the villages, the poorest PMT households remained on the final list, regardless of their perceived poverty level, and the community simply added additional households they felt were poor, up to a predetermined quota. In the other villages, the final list of recipients was determined by asking the attendants to rank both the PMT and additional households up to the quota. This allowed the meeting attendants to replace the PMT households they deemed less poor than other households in their sub-village.

The community verification methods was successfully implemented in 200 experimental villages across 6 districts. In general, satisfaction levels with the method appears high. Community members appreciated that their input was considered in determining who in their villages needed social assistance. In the community verification method, community members particularly thought it was a good method to add the very poor to the list, and ensure that richer households were removed from the list.

Preliminary results indicate that community verification may be useful in targeting very poor households, and particularly useful in updating beneficiary lists in the future. Community verification appeared to bring in poorer households, as households added using the hybrid were about 6 percent poorer than households that would have been on the list simply using PPLS08.

The community appears to be using a different concept of poverty than consumption alone. Surveys of households in the first experiment offer some insight as to what criteria communities use to select beneficiaries. The community appears to be making adjustments for economies of scale; larger households are considered to have higher welfare than smaller ones of the same per capita consumption. Households with more children are also considered poorer.[55] The community may also be considering vulnerability to shocks. For example, for two families with the same consumption, the one that is more connected to the community elite will be ranked 9 percentage points higher in the community welfare surveys than the other, suggesting that more connected households are felt by the community to have better support mechanisms in times of shock. Similarly, households which might be considered 'more deserving' were also more likely to be targeted for a given level of consumption, such as those with lower education, headed by a widow, have a disability, and have serious illness. This is consistent with evidence beyond the experiment; female-headed households are much more likely to receive each of the three major social assistance programs than male-headed households of the same consumption level.[56] Other dimensions found in the first experiment to be used by the community as indicators of non-poverty include connectedness to the financial system and households who have family members outside the village (who can presumably send remittances). Thus, communities appear to be using non-consumption based criteria to target.

There is no evidence that elites select family or relatives, although benefit levels in the first experiment were low. A major concern with community targeting is that people may select their friends and family, rather than the poor. In the first experiment this was explicitly tested for this possibility by having only community elites choose beneficiaries at a small meeting in half of the community targeting villages and neighborhoods, while the whole community was invited to a community meeting in the other ones. No difference in mistargeting outcomes was found, and elite households and those related to them were in fact less likely to be selected in the elite-driven process, regardless of actual consumption levels, than in the broader community process. However, this result is tempered by the low benefit levels involved in the first experiment;[57] elite capture may be more likely when benefit levels are higher, leading to higher incentives to distribute to their own family.

55 These two observations may also reflect a consideration of household potential earnings ability. Households with more members can work more, but not if the additional members are children.

56 See Data Annex.

57 Selected households received Rp 30,000 each, or about $US3, which is about one-sixth of the monthly per capita poverty line.

The follow-up experiment has been conducted in conjunction with the expansion of Indonesia's conditional cash transfer program, which should confirm or reject the absence of elite capture when benefits are high. The second experiment was conducted in conjunction with an expansion of the government's conditional cash transfer program (PKH). Under this program, very poor households with pregnant women, infants and young children, and school-aged children, receive cash transfers conditional on maternal and child health behaviors and school enrolment and attendance. The transfer levels are high, between Rp 600,000 and Rp 2,200,000 per year. When benefits are low, as in the first experiment, it may not be worth elite households diverting funds to their relatives or friends. However, they may be more likely to do so with high PKH benefit levels. The second experiment compares targeting outcomes (degree of mistargeting and whether elite households and their relatives are more likely to be selected as PKH beneficiaries) between community targeting using just the elite and that using a broader community meeting. In addition, an improved PMT model has been introduced that should improve overall targeting accuracy.

The Potential for Community Targeting in Indonesia

These results suggest that communities could improve the effectiveness of the targeting process by being involved in the data collection and beneficiary selection stages. With the possibility of improved identification of the very poor by communities, involving communities in the targeting of social assistance programs could reduce exclusion errors. In addition, the higher satisfaction with targeting outcomes and processes that may result might reduce the informal redistribution of benefits away from official targeting that currently occurs frequently (see Section 1 and earlier in this section).

Nonetheless, careful design and evaluation would be required for its use. Despite the potential advantages of incorporating communities into targeting, the historical results of community involvement have not been successful (see earlier discussion in this section and Section 1). Thus careful design of community-based methods is essential; the approaches used in the field tests described in this section involved significant piloting and training. Large-scale use of community methods should follow only after a process of careful testing.

03

Perceptions of Targeting and Targeted Programs

Program effectiveness requires not only well-designed programs, including their targeting systems, but also public buy-in. Programs must be well designed to be effective. This includes accurate targeting. However, program effectiveness also requires acceptance by politicians, program agencies, local governments and local communities. Obtaining buy-in is important in order to gain political support and be operationally feasible, as well as facilitating stakeholders participating optimally during implementation.

Public buy-in is necessary both for program sustainability and achieving behavior change. Program acceptance by the general public is key to program success, as it generates public support (or at least not hindrance) of implementation. Awareness of beneficiary rights and obligations allows beneficiaries to more effectively utilize benefits, improving program outcomes. Strong outcomes and public support mean politicians and policymakers are more likely to allocate adequate ongoing funds to ensure program sustainability. For example, BLT's sustainability depends very much on parliamentary support, which is driven by the perceptions of the program, regardless of whether these perceptions are driven by policy issues, such as whether unconditional cash handouts are an appropriate poverty reduction strategy, or if they are driven by political considerations, such as how popular the program is, and which politicians and parties it is associated with.

Buy-in is driven by primarily by experience and perceptions. Information about programs is first given through the program information and education activities – the socialization process – which might be official or informal. Local governments, implementers and communities are told what a program is meant to achieve, who it is for, what they will receive, and how it will be targeted. This sets initial expectations and perceptions for a program. The inadequate socialization of current programs has been discussed in Section 1. However, perceptions and ultimately satisfaction and buy-in will depend on the public's experience with a program in action. This can come from their own experience with a program, either as beneficiaries or non-beneficiaries, or through that of others, whether learnt by observation, word of mouth or reported in the media. Buy-in from different stakeholders will ultimately depend upon this public satisfaction and perceptions. This section examines media reporting, and community perceptions and satisfaction.

3.1 Public Perceptions and Satisfaction

Public perception and satisfaction are driven in part by media reporting. The media play an important role in promoting and leading debate on various public policy issues of importance, including targeted social assistance programs. Thus, in addition to formal and informal socialization, public perception and buy-in are also driven by the issues and sentiment the media convey in their coverage about programs, and the volume with which this is done. A media analysis of social programs can help us better understand how public concerns and perceptions of the programs are being shaped by media. Box 3.1 discusses the methodology behind the media results in this section.[58]

Among the three main programs, BLT has the highest and most politicized media profile. During the media study period of 2007-2009, there were 6,470 newspaper mentions of BLT, Jamkesmas, and Raskin, of which BLT received the most attention (57 percent, compared to 31 percent for Raskin and 13 percent for Jamkesmas). The most intensive coverage of BLT was in 2008, when rumors began of government plans to raise fuel prices and re-implement BLT as compensation. The high coverage continued through program implementation in the second half of 2008, followed by politicized discussions in relation to the parliamentary and presidential electoral campaigns in early 2009. Much of the policy debate focused on whether cash handouts reduced poverty or created dependency; whether it is "better to give a man a fish or a fishing rod." During the campaigns, many media articles on BLT were mostly politically related, as parties attempted to exploit BLT's popularity as it provided short-term, just-in-time cash assistance for nearly a third of Indonesian households. Over the same period, Jamkesmas coverage was relatively constant, while Raskin coverage declined in 2009.

58 Community survey data are used for the other results in this section, and are discussed shortly.

Box 3.1: Media Analysis Methodology

This research evaluates 15 national and regional print media in Indonesia. Sampled print media were selected to represent national and regional coverage, various categories of readers, political leanings, and circulation levels.

First, articles with key words are identified. Initial search terms were used to identify articles mentioning programs during the study period. The 6,470 identified articles were checked by analysts to ensure they related to the targeted programs of interest (BLT, Raskin, Jamkesmas). Articles were then compiled in a database so they could be analyzed quantitatively and qualitatively.

A quantitative analysis was then performed, using information about the prominence and nature of the article. The quantitative analysis conducted by the database engine included assessing whether the article was mentioned in the title or first/middle/last paragraph, whether it was straight news, a letter to the editor, a feature, or an opinion piece, how much column space was used, whether it included any visuals, and whether it appeared on the front page or inside the newspaper.

Next, analysts qualitatively categorized each article based on the specific issues discussed. A group of analysts that have been trained on the programs and potential issues then examined the identified articles to determine whether they specifically focused discussion on the programs (focused article) or merely mentioned the programs in the context of other main subjects or issues (mentioned article). Focused articles allow for detailed analysis on how certain issues related to the programs are addressed by the media, whereas mentioned articles provide an understanding of how programs are seen in relation to other issues. A set of key issues and sub-issues were developed to categorize important subject content in articles about the programs.

The sentiment of the article and the disposition of any informants were also assessed. For each article, the analysts also identified its tone based on the overall perception and disposition toward the programs. This reflects the analysts' impression of how the average reader would have perceived each program after considering all of the arguments presented by the journalist or various informants quoted in the article. Only favorable and unfavorable were used as categories, although favorable included neutral and ambiguous opinions, while only critical opinions were considered as unfavorable. Aside from the tone assessment, the study also assessed the favorability of each informant quoted in the article.

A potential perception impact was constructed, being average sentiment for each program of all articles weighted by their potential for impact. The media potential perception impact (PPI) was calculated based on prominence, such as article location and type and presence of visuals, media weight and sentiment. Weights are estimated empirically and set between -10 and +10. The score of article prominence is then combined with the sentiment score (-1 or +1) and media weight to get the PPI index, with value between -50 and +50. The total index as a summation of the PPI of all articles indicates the potential media impact on the public, while the average index indicates media intentions covering issues related to the programs.

In general, policy and implementation issues have received the main media attention. Policy-related issues, in particular the controversy on the effectiveness of programs as poverty reduction instruments, dominated media coverage on BLT (Figure 3.1)**.** Other policy issues included fund allocations, whether complementary programs are needed, and dependency and program exit strategies. Average media sentiment on these issues has been positive for BLT and Jamkesmas, indicating that they are seen to be effective strategies for poverty reduction. The media focus on poverty reduction issues declined over the period as issues relating to program implementation, such as the available stock of Raskin rice and delays in its distribution, and the quality and availability of medical services accessible through Jamkesmas became more pertinent. As mentioned, political interplay articles were also prominent for BLT, such as campaign articles or articles with a political economy bias. The overall focus on policy and implementation indicates that the media were not optimally utilized to convey complete information on programs, their objectives, intended beneficiaries and targeting methods. Articles on these issues made up only 9 percent of BLT articles, 18 percent of Raskin articles, and just 1 percent of Jamkesmas articles.

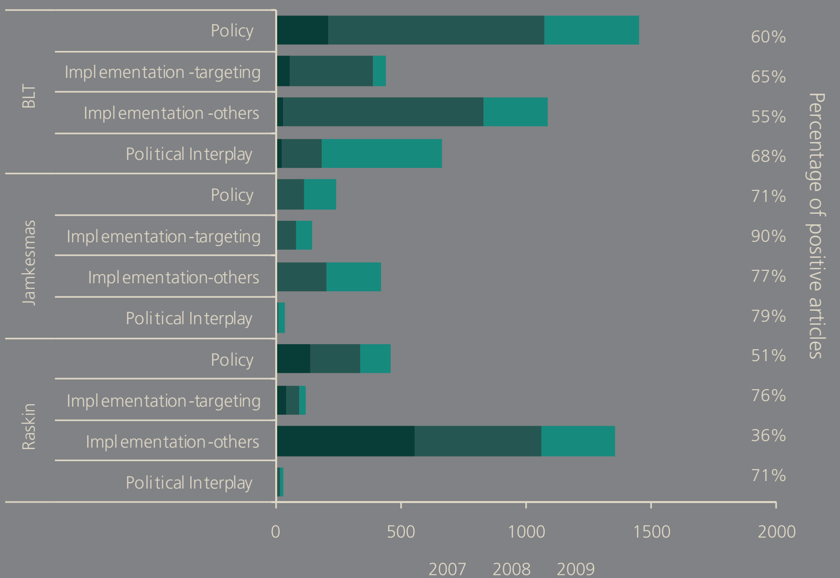
Overall, social assistance programs have generally been perceived favorably in the media, although many of the articles which focus on Raskin are negative. Figure 3.2 presents the media sentiment with respect to each program. The average sentiment trend – comparing the number of positive articles to negative ones – improved for BLT, from 58 percent being positive in 2007 to 61 percent in 2008 and 70 percent in 2009.[59] Examples of positive mentions

59 From a range of -1 to 1, with -1 meaning all articles are unfavorable, 1 meaning all articles are favorable or neutral, and 0 meaning half are favorable and half unfavorable.

include beneficiaries who found the government assistance received during times of high prices very helpful.[60] For the same period, significant increases in favorability were also seen in articles which merely mentioned Raskin in passing (62 percent positive in 2007, increasing to 67 percent in 2008 and 87 percent in 2009), but the sentiments of articles which provided more focus on Raskin were balanced evenly between positive and negative (49 to 50 percent favorable each year). For example, one newspaper reported the theft of the Raskin rice by the village head in Majalengka district in West Java,[61] but in another article quotes a poor mother as saying that while the amount of Raskin rice received was insufficient for her family needs, it was nonetheless a great help.[62] For Jamkesmas, favorable sentiments were generally observed for both focus and mention articles (79 percent favorable in 2008 and 83 percent in 2009).

Policy and implementation issues have received the main media attention recently.

Figure 3.1: Key Issues of Media Focus by Program



Source: Media analysis by MediaTrac

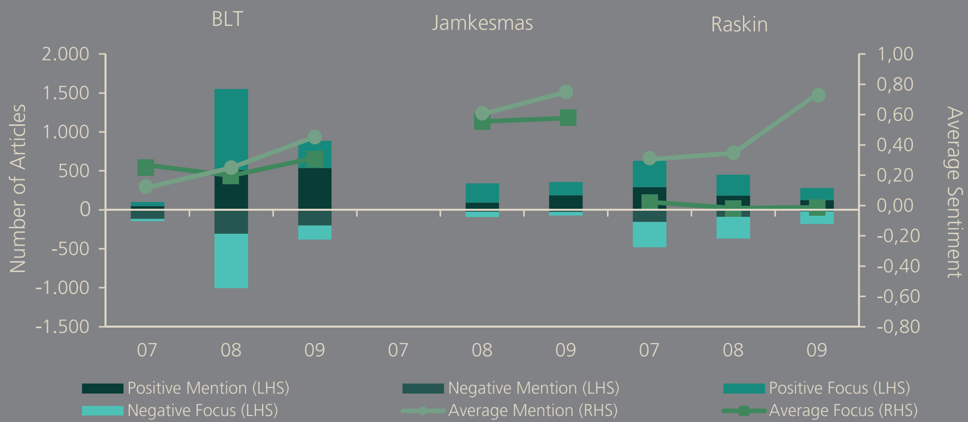
60 Koran Analisa, 14 October 2008.

61 Koran Sindo, 6 September 2008.

62 Koran Sindo, 17 November 2008.

While media sentiment was increasingly positive on average for all programs from 2007-09, there were a number of negative articles, especially for those that focused on Raskin…

Figure 3.2: Average Media Sentiment, 2007-2009

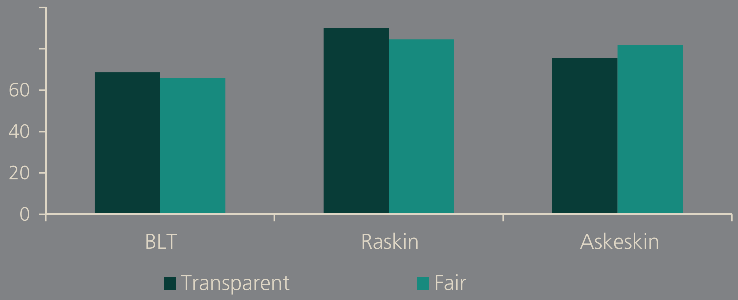


Source: Media analysis by MediaTrac.
Notes: Articles are divided into ones which mention the program in passing (mention) and those which focus on it in more depth (Focus). Articles are qualitatively evaluated as positive (including neutral) or negative in sentiment. Positive sentiment takes a +1 and negative sentiment a -1, and average sentiment is calculated as the sum of sentiment values divided by the total number of sentiments, making average sentiment between -1 (all negative) to +1 (all positive). Jamkesmas was only renamed as such in 2008.

Community members knowledgeable of the programs also generally viewed the programs as having been implemented fairly and transparently. In the IFLS survey, community members knowledgeable of the programs were asked whether they thought the programs had been implemented fairly and transparently, discussing BLT, Raskin, and Askeskin, the previous incarnation of Jamkesmas (Figure 3.3).[63] A clear majority answered affirmatively for all programs. This is consistent with the increasingly positive sentiment we have just seen in the print media toward BLT and Jamkesmas implementation during 2008 and 2009. On the other hand, Raskin received the most positive response of all programs, yet the average media sentiment for Raskin implementation, while fluctuating over time, has remained split between positive and negative overall. The higher satisfaction with Raskin and Askeskin relative to BLT could be related to the greater degree of community involvement in their targeting.

A clear majority of those knowledgeable about the programs in a community thought they had been implemented fairly and transparently…

Figure 3.3: Percentage of Communities Thinking the Programs were Implemented Transparently and Fairly, 2007



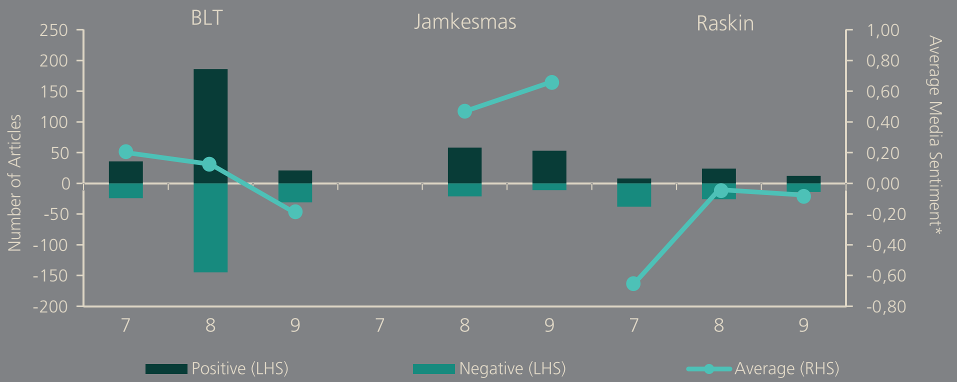
Source: IFLS 2007
Notes: Respondents are randomly selected from amongst individuals in the community considered knowledgeable about the programs. They were asked whether the program was implemented transparently, and whether it was implemented with fairness.

63 We use the 2007 Indonesia Family Life Survey for the community perceptions and satisfaction results in this section. See Box 1.1.

Targeting was not the predominant media focus, but still received attention, with the updated BLT list and under-coverage of the poor the most discussed issues for all programs. Average sentiment on targeting has been positive for Jamkesmas, but neutral or negative for the other programs. Average sentiment towards targeting in Figure 3.4 has been relatively neutral for BLT (ranging from 40 to 60 percent of all articles being favorable), but positive for Jamkesmas (73 to 83 percent favorable). In 2007 only 17 percent of Raskin targeting articles were favorable, but this increased to over 45 percent in 2008 and 2009. Over the study period, the main focus of targeting issues for BLT was the 2008 updated list of beneficiaries. Some articles discussed a perceived inconsistency when post offices distributing benefits compared the list to that in 2005, while others mentioned how non-poor households in 2005 could have become poor since, yet were not on the list. For all programs, exclusion of the poor from the programs was a focus, rather than the leakage to the non-poor. As would be expected, the average tone towards these targeting errors was generally unfavorable, with generally less than 20 percent of articles being positive on the subject for BLT and Raskin. High profile inclusion and exclusion errors received attention, an example of which is an article on BLT which mentions both a widow in Kupang, East Nusa Tenggara, who went to the Post Office to ask why she was not receiving benefits, as well as beneficiaries in Medan, North Sumatra queuing at the Post Office to receive their money while displaying gold jewelry and an expensive cell phone.[64] However, the average sentiment for Jamkesmas under-coverage of the poor was 58 percent favorable in 2008 and 83 percent favorable in 2009, reflecting the greatly expanded coverage of Jamkesmas over Askeskin.

The media sentiment on targeting was roughly neutral for BLT, improving but only to neutral for Raskin, and increasingly positive for Jamkesmas, as Jamkesmas beneficiary levels were significantly expanded.

Figure 3.4: Average Media Sentiment on Targeting Issues, 2007-2009



Source: Media analysis.
Notes: Articles are divided into ones which mention the program in passing (mention) and those which focus on it in more depth (focus). Articles are qualitatively evaluated as positive (including neutral) or negative in sentiment. Positive sentiment takes a +1 and negative sentiment a -1, and average sentiment is calculated as the sum of sentiment values divided by the total number of sentiments, making average sentiment between -1 (all negative) to +1 (all positive). Jamkesmas was only renamed as such in 2008.

The media negativity on under-coverage of the poor is reflected in public complaints of the targeted programs. The percent of communities experiencing complaints over the programs ranged from 25 percent for Askeskin (Jamkesmas), to 56 percent for BLT, with those not receiving assistance being the most likely to complain (Table 3.1). Mistargeting, nepotism and a lack of transparency were the main source of complaints (Table 3.2), the latter an issue driven by poor socialization. This is in contrast to the general acceptance of outcomes among those considered knowledgeable about the programs. According to both IFLS and Susenas survey results, the communities believe the BLT targeting procedure did not reach the intended beneficiaries as well as it should have. Over half of Susenas survey respondents said there were a number of poor households who should have received BLT but did not, and one quarter thought households who received BLT should not have.[65] Such protests were partly due to poor socialization on who should be receiving benefits and how they were selected. In addition, the high level of dissatisfaction with BLT targeting may indicate a link between complaints and the size and nature of the benefit, as well as the level of population covered. BLT provided a high level of transfer, and in cash, compared to Jamkesmas which was contingent on illness, and Raskin, where actual benefits were highly diluted. Moreover, since communities were less likely to redistribute BLT benefits than Raskin, far fewer households received BLT, making it more controversial than Raskin rice which was widely received.

64 Koran Indo Post, 25 May 2009.

65 See World Bank (2012e) for results and discussion.

Complaints were mostly made by those who did not receive assistance… …and the most common complaints were a lack of transparency in beneficiary selection, unfair distribution, nepotism and inclusion of non-poor households.

Table 3.1: Who Complained, by Program (2007)

	Percent of Total Complaints		
Complaints	**BLT**	**Raskin**	**Askeskin**
Those who didn't receive assistance	81	67	76
Those who did receive assistance	7	16	10
Community leader	7	7	3
Village officials	2	2	5
Others	3	8	7

Table 3.2: Reason for Complaint (2007)

	Percent of Total Complaints		
Reason for Complaint	**BLT**	**Raskin**	**Askeskin**
The listing and selection was not transparent	32	21	25
Nepotism practice in the selection	10	9	12
The amount received was not as specified	5	13	6
Assistance was late	2	3	3
Unfair distribution	24	23	26
Practice of illegal fee in the program implementation	1	3	2
Assistance was given to those not eligible	20	16	17
Non-transparent implementation of the program	3	3	3
Other	4	9	6

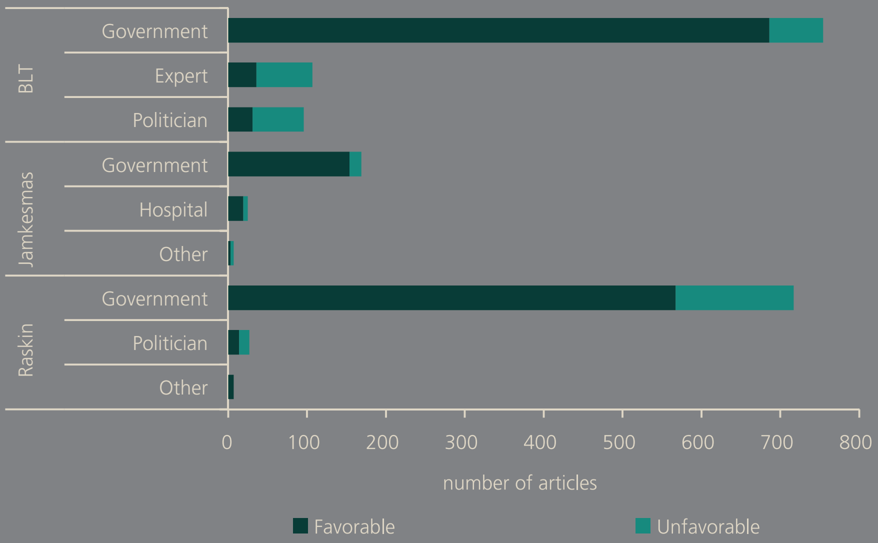
The nature of the protests suggests improved targeting of programs would improve satisfaction and buy-in. Targeting is essential in helping to ensure the intended beneficiaries receive the program benefits, underpinning program performance. In addition, accurate targeting is an important driver of community satisfaction, at least among a significant part of the community.

More effective socialization is also needed. More effective socialization of programs requires activities that will increase active participation and acceptance of programs by stakeholders and support the achievement of program outcomes. For all three main programs, official guidelines need a carefully structured process for socialization, standardized training and implementation, specifying the information which should be socialized, and who should conduct these activities, with sufficient details on the design of the socialization activities and how they should be conducted at different levels. Households need to be aware of where and how they can make a complaint, as well as what the rights and responsibilities are for beneficiaries. Socialization should also focus on targeting, informing the public who targeted beneficiaries are, and how they were selected.

Media reporting of the opinions of key public figures was dominated by government officials, who were mostly favorable towards the programs. For all programs, reported opinion was dominated by government officials (Figure 3.5). Unsurprisingly, the majority of them perceived the programs favorably. For BLT, the strongest unfavorable opinions were voiced by opposition political leaders who questioned the policy behind the BLT program, particularly the program's effectiveness alleviating poverty. Negative sentiment also arose from government officials who criticized distribution delays for Raskin. Interestingly, in the case of Jamkesmas, it was Ministry of Health officials themselves who were the most critical of the program implementation issues, such as the frequency of patients being rejected by participating hospitals.

Media reporting of the opinions of key public figures was dominated by government officials, who were mostly favorable towards the programs.

Figure 3.5: Program Opinion Leaders and Sentiment



Source: Media analysis by MediaTrac.

A more comprehensive approach to media and communication strategy would improve socialization, perception and buy-in. Such an approach requires understanding the target audience, emerging social media, and the different perspectives of program stakeholders. As different target audiences have different perspectives and respond to different media, alternative media campaigns and dissemination tools will be required. The strategic use of different communication channels is important , such as television, radio, pamphlets and local development planning discussions. Communications could be periodically reviewed to meet the changing information-seeking habits of the target audience. Finally, while media plays an important role in forming public perceptions, its current coverage has been mostly limited to implementation issues, with a minimum of program socialization. Therefore it is important to develop a strategy on optimal use of the media, as well as influencing opinion leaders, to drive public opinion as well as deliver appropriate information.

Part B

Improving Targeting in Indonesia

04

Improving Targeting in Indonesia: An Overview

The remainder of the report examines how targeting in Indonesia can be improved. This section identifies issues for improvement, discusses a recent data collection initiative, and proposes a National Targeting System to build upon this. The first part of this report has discussed how targeting of social assistance programs is currently done in Indonesia, and how effective the outcomes have been. The remainder of the report summarizes the how these could be improved. The focus of this second half is outlining a National Targeting System which can serve as the vehicle for making these improvements. We begin in this section by identifying these improvements, discussing the advantages of a recent data collection initiative, and providing an overview of a National Targeting System.

4.1 Areas for Improving Targeting in Indonesia

The main issues facing current targeting in Indonesia are of design and implementation. Table 4.1 summarizes the various problems with current targeting in Indonesia identified in Part A of the report, ranging from the quality of data collection, to methods for selection beneficiaries, to problems of coordination and socialization. We classify them into two main issues: (i) sub-optimal design of targeting methods; and (ii) sub-optimal implementation. Possible improvements are identified.

Targeting design can be thought of as having two components, collection and selection, or which households to collect data from and how to select beneficiaries from among them. The key questions of targeting design are who should we collect information from (data *collection*), and how should we use this information to identify program beneficiaries (beneficiary *selection*). Well-designed collection methods mean the right households are assessed. For example, no matter how accurate a PMT model might be, if a household was not surveyed, then the model can never select it as a beneficiary. Poor households who do not participate in the data collection process automatically become exclusion errors. Once data have been collected from particular households, the second key methodological question is

how we use them to select program beneficiaries. Again using PMT as an example, which variables should be used to construct a household score? How should these variables be weighted? How should these scores be used to identify beneficiaries?

Data collection can be improved in Indonesia. Historically in Indonesia, many poor households have not been assessed. For example, Part A has already discussed which households were surveyed in 2005 and 2008 for BLT. In 2005 most households to be surveyed were identified only through the nomination of the local community head, which may have meant the inclusion of friends and family, and the exclusion of social and political enemies, as well as the exclusion of households not well-known the local leader, who may have been new to the area or socially marginalized. Largely the same households were surveyed in 2008, leading to ongoing exclusion for households who had been omitted in the first round.

Furthermore, methods for selecting program beneficiaries need to be addressed. The different methods used by various programs in Indonesia have all suffered from design issues. Selection of Jamkesmas and Raskin beneficiaries varies by location, but often involves an informal community component that has led to sub-optimal targeting outcomes. For example, Raskin rice is often distributed evenly across the community, regardless of economic need, or at best, according to subjective selection criteria applied in an unsupervised fashion. The use of PMT methods by programs has also been problematic, with the BKKBN PMT using few and poorly selected indicators, and neither the BKKBN and BLT PMT used the statistical techniques adopted widely in other countries.[66] These deficiencies in both data collection and beneficiary selection have resulted in targeting outcomes that either do not favor the poor (BSM), favor the poor but still exclude many poor households (BLT, Jamkesmas), or include many poor but see a greater proportion of benefits received by non-poor households (Raskin).

66 See Section 1 and the technical annexes for more discussion, as well as World Bank (2012b). While the indicators used in the BLT PMT (PSE05) are good indicators, the weighting methodology was ad hoc.

Targeting outcomes have also been affected by inconsistencies between program beneficiary selection as well as with local poverty rates. The use of different collection and selection methods by each program has meant that despite three of the main programs having the same target population, less than a third of these households received all three programs (BLT, Jamkesmas and Raskin; see Section 2). Thus, even if the current social assistance programs were considered a sufficient overall approach to assisting the poor and protecting the vulnerable, most of these households do not receive the complete package. This is compounded by an inconsistency in beneficiary numbers by district with actual district poverty rates, meaning in many districts the budget and beneficiary allocation falls short of that required for the number of poor and vulnerable in those locations, but is exceeded in other locations. A simple rebalancing of district allocations in line with district poverty rates could significantly improve targeting outcomes.

Implementation problems have also badly affected targeting outcomes in Indonesia, in particular a lack of coordination between ministries and poor socialization. Implementation is as important as design in determining the effectiveness of program targeting. Well-designed targeting will remain ineffectual if not implemented successfully. Part of the report has already discussed a number of implementation problems which have hampered targeting effectiveness in Indonesia. These include targeting processes which vary significantly from official guidelines for all programs and in many districts, ineffective socialization, and a lack of coordination between agencies and programs. Ineffective socialization has had a number of adverse effects on targeting and program outcomes. Section 1 has discussed the limited socialization that has generally been conducted for most programs. This has adversely affected targeting outcomes. Little or no socialization of program objectives and targeting methods, especially to the local government level, has contributed to the deviation from official targeting processes discussed earlier. Moreover, poor communication of targeting objectives and methods has been a factor in community protests over inclusion and exclusion errors, due in part to a lack of understanding of who should be receiving benefits and how they have been selected (see Section 3). It has also played a role in communities informally redistributing benefits to non-target households, especially for Raskin, as has poor socialization of the rights and responsibilities of beneficiaries.

Coordination between agencies has been difficult due to a lack of an overarching institutional framework for social protection. There are a range of program functions that would be more effective if integrated across programs. These include a coordinated complaints and grievances process, and integrated socialization and monitoring and evaluation functions, as well as program designs which take into account the benefits offered by other programs.[67] However, there is no clear framework governing institutional arrangements which facilitates coordination and integration between planning and implementing agencies, whether central or local. This also affects targeting. For example, PKH would be a more effective program if the all beneficiaries also received Jamkesmas, as this would allow them to fulfill their health-related conditionalities without paying service fees. However, in the past Kemenkes and Kemensos have not coordinated their beneficiary lists to ensure beneficiary overlap.

67 See World Bank (2012d) for further discussion.

A range of key design and implementation issues adversely affect current targeting outcomes in Indonesia.

Table 4.1: Key Issues with Current Targeting in Indonesia

Key Issue	Problem	Possible Improvement
Design Issues		
Sub-optimal Data Collection	Not all poor and vulnerable households are assessed when collecting information on potential beneficiaries. Households excluded from assessment are then excluded from programs.	Use a wider range of methods to identify potential beneficiaries for assessment. Incorporate existing program lists and national surveys in data collection process.
Sub-optimal Beneficiary Selection	Methods to select beneficiaries can be improved. Community involvement is usually informal and unstructured, and often results in benefits being received by non-target households. PMT scoring has historically not followed international best practice.	Identify optimal design for each selection method. Determine in which circumstances each method most appropriate.
Lack of Synchronization with Macro Poverty Data	There are inconsistencies between program beneficiary numbers and local poverty rates, meaning some districts receive too small an allocation, and some too large.	Make allocations consistent with known local poverty rates from macro poverty data (e.g. Susenas or Poverty Maps).
Implementation Issues		
Deviation from Official Targeting Processes	Implementation of targeting processes in practice has deviation from official guidelines for all programs. This has often resulted in increased inclusion and exclusion error, as well as dilution of benefits received.	Better socialization of intended targeting objectives and methods to all levels of implementers, communities and beneficiaries. Improved monitoring and evaluation of implementation.
Poor Agency Coordination	Programs which would have effectiveness enhanced from coordinated lists often have different beneficiaries.	Coordinated targeting of programs with complementarities. Development of clear institutional framework covering targeting.

4.2 Improving Data Collection: PPLS11

The accuracy of any list of the poor depends critically on how data are collected and which households are surveyed. Improvements over simply revisiting the 2008 list are possible. We have already discussed the importance of data collection to targeting outcomes. This can be illustrated by simulating a program targeting the poorest 30 percent of households using the 2008 Statistics Indonesia PMT specification (Box 4.1 summarizes the key steps in conducting a PMT, and Box 4.2 discusses its historical use by Statistics Indonesia). Here we contrast surveying only households from the 2008 list with surveying all households. The results indicate that inclusion and exclusion errors are considerably lower when all households are surveyed, despite exactly the same PMT selection mechanism, and the targeting gains are 20 percentage points higher (Figure 4.1). Surveying all households is too costly and time consuming in most countries, but represents a benchmark against which data collection designs can be evaluated. Thus, data collection strategies ask how we can avoid visiting all households while still including as many poor ones as possible, bearing in mind that surveying anything less than all households is likely to increase exclusion error.

The effectiveness of the 2008 PMT can be significantly improved upon if the right households are surveyed to begin with.

Figure 4.1: Targeting a Program at the Poorest 30 Percent Using the 2008 PMT: Revisiting the 2008 List versus Surveying the Whole Population

Sources: Susenas, World Bank calculations.
Notes: Results are from simulating a program targeting the poorest 30 percent. "Revisiting 2008 List" means only households on the 2008 list have the PPLS08 PMT applied to them in the Susenas data (households receiving BLT are used to as a proxy for this list), and therefore all other households cannot become beneficiaries. "Visiting All Households" means all households in the survey have PPLS08 PMT scores constructed. "Inclusion Error" is calculated with the poorest 30 percent of households by per capita consumption as program targets. "Exclusion Error (10) (20) and (30)" are the percentage of poorest 10 percent, 20 percent, and 30 percent of households, respectively, excluded from the program. "Targeting Gain (30) (40) and (50)" are the gains over random targeting out of 100 percent, calculated when using the poorest 30, 40 and 50 percent of households respectively as target populations.

Box 4.1: How to Construct a Proxy Means Test (PMT).

PMT estimates household economic status without the costly process of conducting a full consumption survey. Instead, a small number of household characteristics are collected from households, either by home interviews, or another form of data collection with subsequent physical verification. Statistical techniques are then applied to the collected indicators to construct a score estimating household economic status. Once each household has a PMT score, these scores can be used to select beneficiaries for social assistance programs. This box briefly summarizes how to implement a PMT. For greater detail, see World Bank (2012b).

The first step in designing a proxy means test is to select indicators. PMT indicators need to be well-correlated with poverty, consumption or income, in order to act as a proxy for household economic status. In addition, to be suitable for PMT, they should also have three further characteristics: (i) few enough that it is feasible to survey a potentially large proportion of the population with a relatively short questionnaire; (ii) easy to measure or observe; (iii) relatively difficult to manipulate in order to get a better score. In addition, for scoring purposes (discussed shortly), these indicators will also ideally be included in national household socio-economic surveys, such as the Susenas in Indonesia, which includes detailed household consumption. While the final choice of variables to use in PMT depends on local context, there are a number of indicators which are common in PMTs around the world. These include the quality of dwelling construction and other housing characteristics such as use of electricity and cooking fuel type, ownership of durable goods, the demographic structure of the household, and education and employment characteristics. Sometimes community-level variables are included as well, such as the presence of a health center. The number of underlying variables used is generally around 10 to 20.

Once the indicators have been collected from each household, they are weighted to create a household PMT score. There are several methods for weighting the indicators. Where national socio-economic household surveys with household income or consumption are available, such as the Susenas in Indonesia, a common approach is to regress household income or consumption directly on the selected variables. Often these regressions are run separately by region (e.g., by province or rural/urban) so that variable weights differ across regions. In Indonesia a per capita consumption regression which is used to obtain PMT scoring coefficients. When such survey data are not available, other statistical techniques can be used to weight the indicators into a score. One of the most common methods is Principal Component Analysis (PCA). See Wai-Poi (2011) for a survey of alternative weighting approaches, their relative effectiveness, and when each should be employed, with examples from Indonesia. Whichever method is used to construct scoring weights, a number of different models will need to be examined, to see which specifications result in the lowest predicted targeting errors. Specification choices include which geographical level of aggregation to use, which households to include in the scoring model (i.e. all households, or only those below a certain consumption level), and which variables to retain. These questions are discussed in the Indonesian context in Section 6 of this report.

From the constructed PMT scores, households need to be identified as eligible or not eligible as program beneficiaries. Households can be ranked by PMT score, across the whole country or within a region. Those with scores beneath a certain threshold, often associated with a poverty line or consumption level, can qualify as eligible, or a program could select the lowest ranked households up to a program quota. The PMT score criterion may also be combined with demographic criteria in the case that only certain types of households are targeted by a program, such as a conditional cash transfer program aimed at households with pregnant women, infants and school-aged children. How program beneficiaries can be selected from PMT scores is examined in Section 6.

PMT avoids the difficulties and costs associated with collecting and verifying household income or consumption. However, it requires a relatively high degree of technical capacity to design and implement, and because it is based on statistical models, has inherent error. In addition to the design of PMT in Indonesia (World Bank 2012b), a comprehensive description of the required steps in the PMT process can be found in Narayan and Yoshia (2005), and in Sharif (2009) along with implementation considerations. For a critical view of PMT and its disadvantages, see Kidd and Wylde (2011).

A very large data collection of potentially poor and vulnerable households was collected in mid-2011. This has the potential to serve as an improved initial basis for the unified registry. In collaboration with the National Team for Accelerating Poverty Reduction (TNP2K) in the Vice President's office, Statistics Indonesia recently updated its list of the poor in the second half of 2011, called PPLS11. This update could be ideal to serve as the basis for a unified registry, covering up to 40 percent of the country. The remainder of this sub-section looks at how PPLS11 was collected and what improvements in accuracy might be expected. (Box 4.3 summarizes alternative possibilities for establishing an initial database).

The 2011 data collection (PPLS11) covers around 40 percent of Indonesian households, and represents an expansion in both coverage and scope of data collected. The 2011 Statistics Indonesia data collection of poor and vulnerable households represents a significant expansion from previous years (Box 4.2), increasing the number of households surveyed from around 19 million in 2008 to 25 million, or around 40 percent of all households. The government's objective is that PPLS11 includes as many of the poorest 40 percent of Indonesians as possible, and can be used to target all social assistance programs. In addition to increasing the number of households surveyed, a broader range of demographic data are being collected as well, which can be used as targeting criteria for different programs. Additional indicators are also being collected which may improve the accuracy of the PMT scoring; their effectiveness is discussed in the Optimal Proxy Means Tests technical annex. Most importantly, in 2011 the previous list was not simply revisited, as it largely was in 2008, meaning new households could enter the list.

Box 4.2: Statistics Indonesia has been collecting a list of the poor every three years since 2005, making improvements each time. In 2011 a new and potentially more accurate list was collected, which could serve as the basis for the unified registry in Indonesia.

When BLT was launched in 2005, Statistics Indonesia (BPS) collected a new list of the poor to determine beneficiaries. Previously, the national list of the poor was from the National Family Planning Board (BKKBN). The BKKBN list was based on household assessments using five indicators, not all of which were based on economic status. The 2005 BPS list, PSE05 (*Pendataan Sosial Ekonomi Penduduk*), improved on the previous list by using 14 household and housing indicators, and statistical scoring. Despite being successfully collected in a very short time, and subsequently determining beneficiaries for BLT, as well as district quotas and in some places beneficiaries for Raskin and Jamkesmas, it suffered from two weaknesses. First, generally only households who were nominated by sub-village heads were surveyed with the PMT questionnaire. This meant that many poor households were excluded. Second, while the PMT was an improvement on the BKKBN approach, internationally standard scoring systems were not used. At this time, Statistics Indonesia conducted both the data collection and beneficiary selection process.

In 2008, after Statistics Indonesia updated the PSE05 list for the second BLT, removing households which had moved or all of whose members have died, and adding a small number of new households, they revisited the new list with another PMT questionnaire. This new data collection was PPLS08 (*Pendataan Program Lingdungan Sosial*). Statistics Indonesia improved upon PSE05 by using an international best practice PMT. Household indicators were collected and combined with village indicators from existing survey data, and PMT scores were direct estimates of household consumption, with weights coming from a consumption-based regression. The new PMT represented a significant improvement (see World Bank 2012b and Technical Annex 2 of this report). However, as the households surveyed were largely the same ones visited in 2005, PPLS08 continued to exclude poor households who had not been visited in 2005, and also missed any households who had fallen into poverty since then.

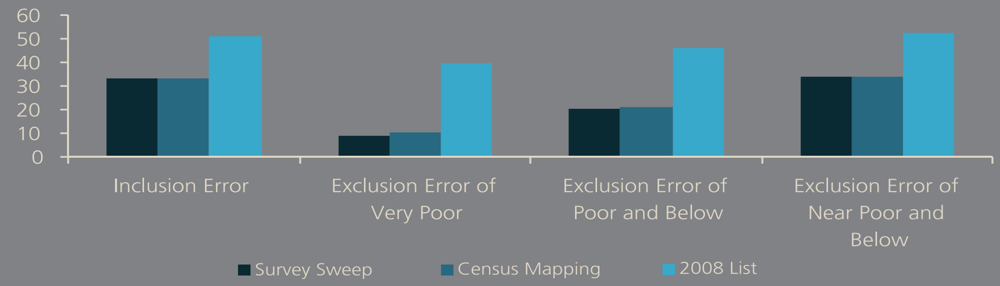
In 2011, Statistics Indonesia collected PPLS11. Reassessing which households to survey (data collection) could mean a more accurate list of the poor that would improve targeting outcomes in Indonesia significantly, and might serve as a basis for a unified registry of potential beneficiaries. As importantly, the working group of National Team for Accelerating Poverty Reduction (TNP2K) has worked with Statistics Indonesia to construct the PMT scores, and TNP2K alone will select program beneficiaries from the registry, rather than Statistics Indonesia, further moving the institutional arrangements in Indonesia in line with international best practice (see discussion later in this section).

PPLS11 used a combination of the PPLS08 list, pre-listed households based on 2010 Census data, and new households referred by households on these lists. To improve upon the known exclusion errors of the 2008 list, Statistics Indonesia and TNP2K designed the 2011 list to visit both households from the 2008 list and households pre-listed from an analysis of the 2010 Population Census. To pre-list households from the Census, simplified PMT models were constructed and a household consumption estimate made for the entire population. Household estimated to be in the poorest 45 percent nationally were used as a pre-listing of households for PPLS11. About 70 percent of the final PPLS11 households came from this pre-listing. Households from the 2008 list which were considered very poor or poor on the 2008 list but not amongst those pre-listed from the Census were then added to the survey listing in the field. In addition, a meeting was held with three poor households in each village, and the household representatives were asked to nominate other households they considered poor which were not already listed to be surveyed.

Analysis suggests that using household listings based on the 2010 Population Census could lead to targeting outcomes close to those of a national survey sweep at a much lower cost. As the Census has a number of indicators suitable for a reasonably accurate PMT, and it covers the entire country, using it to pre-list a survey frame could result in similar targeting outcomes to employing a national survey sweep, but at a much lower cost. We examine the simulation results of applying the same PMT scoring to three different sets of households in the Susenas survey data. The first approach is a survey sweep, which applies the PMT to all households. The second is the Census Mapping approach, which first estimates the poorest 40 percent of households using a simplified PMT based on the indicators available in the Census, then applies the full PMT to those households to rank within this list. The final method simply applies the full PMT to those households on the 2008 list. Figure 4.2 presents the results of using each approach to target a program for near-poor and below households. Since households not on the 2008 list cannot be assessed with the new PMT in 2011 under the third approach, exclusion rates amongst poor and near-poor households range from 40 to 50 percent. As expected, when we allow all households to be assessed by the PMT (survey sweep), then these errors fall to around 10 to 30 percent. However, despite restricting full PMT scoring to less than half of all households under the Census pre-listing approach, estimates of the exclusion errors are very similar to those of survey sweep. This suggests that the PPLS11 list could result in significant targeting improvements over PPLS08.

Conducting a PMT survey on a household poverty mapping based on the 2010 Census could lead to similar targeting outcomes as a national survey sweep, but at a much lower cost.

Figure 4.2: PPLS08 PMT Applied to Different Data Collection Methods: Survey Sweep, Census Mapping, and 2008 List



Sources: Susenas, World Bank calculations.
Notes: PMT was applied to different subsets of Susenas. "Survey sweep" was all households. "2008 List" was BLT households, a proxy for being on the PPLS08. "Census Mapping" applied a PMT based on variables common to Susenas and Census to identify the poorest 40 percent of households, and then applied the full PPLS08 PMT to these households.

The use of the 2010 Population Census is a relatively low cost and practically feasible approach, but is not used in other countries due to two serious issues. Applying PMT and poverty mapping techniques to a dataset the size of the Census requires high technical capacity and is time consuming, but the total costs of pre-listing the 2011 survey using this approach are relatively low. However, the quality of Susenas data used in the simulations above is considerably better than that of the much larger Census, and so actual targeting outcomes may not reach these estimates. More importantly, this approach is not used elsewhere in the world for two main reasons. First, in many countries there are tight legal restrictions on how census data can be used, and strict confidentiality clauses explicitly exclude certain data uses. Second, there is a reputation risk for the statistical agency, in that if households believe either the census or other surveys conducted by the agency can be used to determine program beneficiaries, they may lie or manipulate responses in the future, even on unrelated surveys.

These risks exist in Indonesia as well, but possibly to a lesser degree. Indonesian Census data are also confidential, but no explicit representations are made as to how the data will and will not be used. This allows the possibility of confidential use of Census information for official purposes. In addition, final beneficiary selection is made upon the basis of the new PMT data collected and scored during PPLS11, not from the Census information itself. More importantly, with Statistics Indonesia already being widely known to identify BLT (and PKH) recipients, the reputational costs and possibility of false survey responses is already borne to some extent. Thus using the 2010 Census data represents a cost-effective approach to improving targeting outcomes in Indonesia in the short-term, while the leadership of TNP2K in developing the NTS and producing program beneficiary lists is a key step in the targeting reform trajectory of removing reputational risk for Statistics Indonesia (see Box 4.2). However, the need for continued targeting technical capacity building in agencies outside of Statistics Indonesia must be emphasized.

Box 4.3: There are various alternatives for collecting initial data for a National Targeting System.

Data collection for a multi-program database can come from three main processes. The first is to use beneficiary data from any current programs that have demonstrated good targeting outcomes, which are in electronic form (or could be put in electronic form at low cost). Second, data are taken from stand-alone targeting systems or databases that can be used by different programs. These data can be of individuals or households, using statistical methods of assessments such as proxy means-tests, and of groups or areas, as with poverty maps. Third, other data, such as tax and property records, can be used as cross-checks to identify non-poor in program databases that should be excluded from social programs.

Existing data from any current well-targeted social programs can be used by other complementary programs for targeting purposes. In many cases, however, these data are not kept in electronic format, or the electronic files are hard to merge with other databases. This is often the case with social assistance programs in OECD countries (Grosh *et al.* (2008)), and thus is likely to be more difficult in developing countries. These data are also usually considered confidential and not easily accessible by other programs.

Some overseas programs have built a large database of beneficiaries over time that can be used by other programs. Mexico's Conditional Cash Transfer program *Oportunidades* contains more than five million beneficiary families that have received transfers to promote health and nutrition activities, and enrollment and regular attendance of children in elementary and secondary education. This database has recently been used to identify elderly poor families without children to provide them with cash assistance for food and other necessities. Such databases can also be used to identify poor households not affiliated with the subsidized health insurance program and other complementary programs (Table 2.1 suggests that such opportunities exist in Indonesia).

Other countries use data on prospective beneficiaries from a stand-alone national targeting system. Some countries have created a national targeting system and database. Chile pioneered this approach by developing the *Ficha* CAS system in 1979 to target a host of local and national direct social assistance programs for the poor (for a review of the *Ficha* CAS system see Larranaga (2003). This database is now used to target the Family Assistance Subsidy (SUF), non-contributory pensions, housing voucher subsidies, and conditional cash transfer programs. Colombia also has a stand-alone national targeting system, the System for Selection Beneficiaries of Social Programs (SISBEN), developed in 1994. SISBEN is used to target large national programs, including the subsidized health insurance for the poor program that covers nearly 19 million people (nearly 60 percent of the population), the conditional cash transfer *Familias en Accion* program that covers nearly three million families (30 percent of the population), and many other national and local programs. Brazil introduced the *Cadastro Unico* system in the early 1980s to target national programs such as the *Bolsa Familia* program, which covers more than 11 million families and is used for other state and local programs. The Philippines is also developing a National Household Targeting System for Poverty Reduction (NHTS-PR), which is used to target conditional cash transfer programs, and will also be used by a variety of other national programs (World Bank 2009). Indonesia is pursuing this approach.

4.3 Rationale for a National Targeting System

PPLS11 alone cannot provide all of the improvements required for better targeting outcomes in Indonesia. We have seen that PPLS11 potentially offers significant improvements in data collection compared to earlier targeting in Indonesia. However, the use of PPLS11 alone cannot deliver the full range of improvements identified in Section 4.1, especially those regarding implementation issues.

The remainder of the report proposes a National Targeting System in Indonesia, and outlines the various functions required under such a system. In previous sections of this report, we have reviewed how targeting is currently designed and implemented in Indonesia for major household social assistance programs, how accurate it is, how it has been socialized and perceived, and what we know about the potential contribution of communities to targeting in Indonesia. The remainder of the report outlines a National Targeting System (NTS). An NTS is a coordinated and centralized targeting system which can be used to target most household-based social assistance programs. This section discusses the advantages and disadvantages of such a system before providing an overview of the major components.

The Advantages, Disadvantages and Political Economy of a National Targeting System

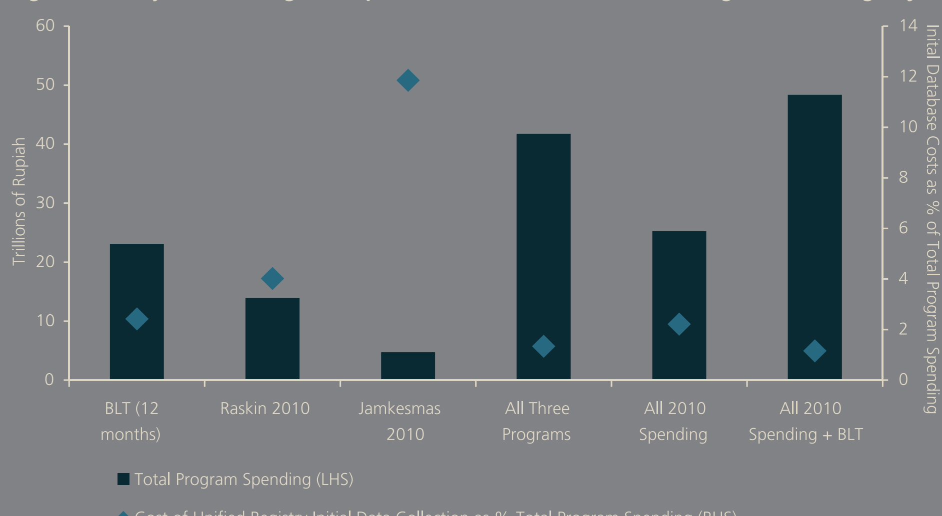
An NTS could improve targeting and program effectiveness in Indonesia. There are several benefits related to establishing an NTS. A unified targeting registry could be constructed using improved targeting methods. With this single source of quality-controlled data, programs can use their preferred criteria to extract more accurate beneficiary lists and improve targeting outcomes. The registry could be integrated with higher level poverty data to guide program quotas at a local level. Moreover, programs with the same target population will have consistent beneficiary lists, which they currently do not (see Section 2). This will lead to better complementarities between social assistance programs, such as PKH beneficiaries who receive cash transfers conditional on appropriate attendance at health facilities can also be Jamkesmas beneficiaries, allowing them free access to these services. Moreover, an NTS can be used to link with other potential program areas, such as agricultural extension services, financial inclusion efforts, and household-specific subsidies. In addition, an NTS can lead to reduced fraud, corruption and duplication, as well as better facilitation of program exit strategies.

Furthermore, targeting social assistance and insurance programs with a single mechanism also facilitates an examination of the overall suite of social protection programs. When all or most programs are being targeting by an NTS, it becomes natural to think about the benefit packages as a whole. Who is eligible for multiple programs? Do the total benefits aggregate to a sensible support package and provide complementary coverage? Or are there overlapping programs or gaps in coverage? These are important discussions in designing a coordinated and effective approach to social protection, and the development of an NTS can provide the impetus to initiate dialogue within government and with supporting parties.

The costs of a unified registry would represent a very small proportion of total program spending. A unified registry can be used by multiple programs in different ways depending on targeting objectives, realizing economies of scale, with a lower targeting cost per program per beneficiary. Total central government expenditures on household-targeted social assistance were budgeted at Rp 25.2 trillion (US$ 3 billion) in 2010, which was 3.6 percent of total central government spending, having reached as high as 6.7 percent in 2006 when BLT was active. The estimated cost of the initial data collection for a unified registry is around Rp 560 billion. This would represent around 4 percent of Raskin's and 12 percent of Jamkesmas' 2010 total program budgeted expenditures, or 2 percent of a 12 month BLT (see Figure 4.3). If all three programs were to use the registry, the costs of initial collection would represent just over 1 percent of all annual program costs. Ongoing annual costs for updating household data over time and maintaining an appeals system are likely to be lower than initial collection costs, but even at the level of initial costs, total annual targeting costs remain very low relative to total cost of benefits transferred.

The initial cost of a unified registry represents between 2 and 12 percent of each program's total expenditures, and just over 1 percent of the three major programs combined, making the incremental cost of targeting very low if it can effectively direct the remaining funds to those households who need it most.

Figure 4.3: Major Social Program Expenditures, and Cost of Constructing a Unified Registry



Sources: Susenas, World Bank calculations.
Sources: Ministry of Finance, World Bank calculations.
Notes: 2010 data are based on the budget (APBN). BLT for 12 months is total cost of BLT in 2005-06. All three programs is Raskin and Jamkesmas 2010 + 12 months BLT. All 2010 is all household-targeted social spending.

However, there are risks to targeting all programs from a unified registry which require consideration and mitigation, in particular that some poor households will be systematically excluded from social assistance. The most significant risk in using an NTS to target most or all major social assistance programs is that poor households who are not on the registry, or have been mis-evaluated as non-poor, will miss out on most assistance. This is a genuine risk with significant adverse effects for excluded poor households. However, while a program targeted at the poorest 10 percent of households (similar to PKH) can expect exclusion errors of up to 50 percent, these households would also be eligible for programs targeted at a broader population base, such as Jamkesmas, BLT and Raskin. The percentage of households below the national poverty line likely to be excluded from these other safety net programs is more likely to be around 15 percent, while around 30 percent of the near-poor would be excluded, which compares favorably to the current exclusion rates for BLT and Jamkesmas of over 50 percent. Thus, the risk and impact of being excluded from major programs under an NTS is less than for current targeting, while households who do become beneficiaries will benefit from the entire support package that it is intended they receive. Moreover, this risk could be mitigated if considerable emphasis is placed on designing and implementing appropriate and effective complaints and grievances systems, discussed in Section 7.

In addition, the technical and political challenges of implementing a National Targeting System should not be underestimated. The process of implementing a National Targeting System is slow and complex. The technical challenges can be significant, and achieving political cooperation between agencies takes time. Moreover, there is not a standardized approach that can be adopted from other countries. Rather, each country must adapt the general principles to its particular context.[68]

The relatively high administrative capacity required to implement a PMT-based system is less of a constraint in Indonesia in the short-term. Designing and implementing PMT requires reasonably high administrative capacity (Coady, Grosh and Hoddinott 2004; Grosh *et al.* 2008). This is an important disadvantage for PMT in many developing countries. For example, an evaluation of a pilot for a national PMT survey in Pakistan identified a number of implementation issues, including confusion over certain indicators, insufficient socialization at the community level, an overreliance on local knowledge in determining which households to survey, and exclusion of marginalized groups (GHK 2009). Such considerations are less of a constraint in Indonesia, where Statistics Indonesia has conducted two major PMT exercises in 2005 and 2008, in addition to the current 2011 work (previously discussed; see also Box 4.2). However, should a different agency than Statistics Indonesia become responsible for the PMT data collection and updating activities in the future, then whether there is sufficient capacity in that agency becomes an important question (Section 5.2 discusses the possible risks in having the national statistical agency conduct targeting); GHK (2009) highlighted lack of implementing capacity as one of the key issues in the Pakistani experience.

Ensuring cooperation between government ministries is critical and can be difficult. The support of program implementing line ministries is required to help ensure beneficiary lists from the NTS are to be used at the local level. We have seen in Section 1 that such central lists are often not used locally. In addition, MIS units within line ministries will need to work closely with the NTS MIS unit to ensure proper data sharing arrangements. This is essential if the initial beneficiary details from the NTS are to be useful for line ministries, and for final beneficiary details to be communicated back to the NTS. This is particularly true in the case that existing beneficiary lists need to be incorporated into the NTS when the unified registry is first being developed.

The risk of information manipulation is also increased. Targeting usually involves obtaining information from prospective beneficiaries, thus creating the incentives for households to misreport. Criticism can be made about a system that rewards cheating, and any attempts to exclude cheating may also weed out genuine applicants (Sen 1995). This issue of information manipulation is potentially increased under an NTS. When more benefits are allocated by the targeting system, there is a greater incentive for households to manipulate the information used for calculating poverty scores. The more programs that are targeted by an NTS, the greater this risk becomes. The risks also increase over time, as households learn which type of information becomes influential in identifying beneficiaries. One way of mitigating this is to keep the scoring system confidential, as is done in Chile.

Other potential social costs of targeting can also occur with an NTS, although the evidence for these problems in Indonesia is mixed. In addition to information distortion, other social costs of targeting can include stigma, incentive distortions and negative impacts on community cohesion (see Sen (1995) and Kidd, Calder and Wylde (2010)). There has been little evidence of a stigma of poverty attaching to beneficiaries of social assistance in Indonesia, nor of beneficiaries adopting negative behaviors in response to receiving assistance, such as working less, or increasing expenditures on tobacco. In fact, PKH benefits were largely spent on higher protein foods and increased health expenditures, and BLT benefits were spent on basic necessities such as rice, one-off educational expenses, or health expenses, with no

68 See, for example, Casteneda and Lindert (2005) for a survey of Latin American and US targeting systems.

significant change in tobacco expenditures between PKH and BLT beneficiaries relative to non-beneficiaries (World Bank 2012e, 2012i). At the same time, BLT households saw decreased child labor,[69] experienced no decrease in BLT household working hours compared with non-BLT households, and in fact found new jobs at higher rates (World Bank 2012e). However, the history of targeted social programs effects on social cohesion, which has sometimes been negative in other countries,[70] has been mixed in Indonesia. There have been positive effects, such as a multiplier effect expenditures for non-BLT households in areas with more BLT beneficiaries (World Bank 2012e), and a shift in spending amongst non-PKH households in PKH areas to include more on health (World Bank 2012e), both positive indicators for social cohesion. However, there have been well-documented conflicts over targeting outcomes for BLT (Section 1), and BLT targeting has often been a source of complaint (Section 3).[71] While an NTS can improve targeting outcomes and thus reduce conflict, the issue discussed previously of some poor households being systemically excluded from all programs could increase the chance of conflict, or the informal redistribution of benefits at the local level.

More generally, it has been argued that targeting the poor fails to develop the broad-based political and social support which more expensive but universal programs can achieve, which in turn also cover more poor households. It has been argued that targeting the poor might prevent greater spending on universal programs for pensions, child grants, and covering the disabled or widowed, which may have resulted in greater benefits to the poor, albeit at a higher fiscal cost (see Box I.1 of this report, World Bank (1990), Mkandawire (2005), Kidd, Calder and Wylde (2010), Kidd and Wylde (2011)). Sen (1995) has suggested that "benefits meant exclusively for the poor often end up being poor benefits." Categorical programs which have universal eligibility for all individuals or households in the demographic target can reduce the number of poor households excluded, especially in the case of child grants, as poor households tend to have more children.[72] Moreover, social conflict due to targeting is eliminated under universal programs.

However, support for universal non-contributory programs is unlikely to develop in Indonesia in the short to medium term. Instead, the focus is likely to be on universal coverage through a mix of contributory and targeted programs, with expanded coverage of the latter important. As discussed in the introduction, Indonesia's household-targeted social assistance spending is currently only 0.4 percent of GDP. It is highly unlikely that more costly universal non-contributory social programs will be implemented in the next ten years. Rather, the focus of the SJSN in Indonesia is on universal social insurance coverage, but with some households (particularly those in the formal sector) making contributions, and only poor and vulnerable households having premiums paid for by the government. With recent laws passed to begin these programs in 2014 and 2015, any universal non-contributory framework is not imminent. Thus, there is currently considerable political support for government targeting of poor households under the SJSN framework.

4.4 Overview of a National Targeting System

There are numerous components to a National Targeting System, which relate to the design, implementation, maintenance and updating, and future developments of such a system. At the heart of an NTS is a unified registry of potential and actual beneficiaries. However, it also requires a legal and institutional framework to support it, and many supporting functions, which include a complaints and grievances system, socialization and communications, monitoring and evaluation, and consideration of the possible relationship between the NTS and program exit strategies. These different functions can be categorized as being part of the design, implementation, or maintenance of the NTS, or relate to the future evolution of the system. Table 4.2 summarizes these essential components. We look at each of these in turn in the remainder of this report.

69 Limited impact on child labor and weekly hours of education were found for PKH (World Bank 2012i).

70 Kidd and Wylde (2011) cite Adato (2000), Adato et al. (2000), Adato and Roopnaraine (2004) as evidence.

71 There is also some anecdotal evidence of protests over PKH targeting (Hannigan 2010).

72 However, Acosta, Leite and Rigolini (2011) have conducted simulations for 13 Latin American countries that poverty targeted programs can deliver greater benefits to the poor than a categorical program for the elderly or children of the same fiscal cost. It should be noted that their simulations assume a program equivalent to 0.5 percent of GDP, with 15 percent additional administrative costs, and an exclusion error of 30 percent. If this were a single poverty-targeted program, then the exclusion error assumption is consistent with best practice PMT results from international experience. However, if 0.5 percent of GDP represents a number of smaller programs covering fewer people, then exclusion errors are likely to be higher.

A unified registry is just one component of a National Targeting System, all of which are required to improve targeting effectiveness and increase public buy-in.

Table 4.2: Components of a National Targeting System

Component	Notes
Design	
Targeting Objectives	What are the targeting objectives of different social assistance programs? How do these different objectives affect NTS design considerations?
Legal and Institutional Framework	Which agencies are involved in the NTS, what are their roles and responsibilities, where will the permanent unit which manages the NTS be located, and how will it be staffed and funded? Who collects data, who uses it and who maintains it?
Initial Data Collection	How is the initial unified registry developed? What methods are used to collect household data?
Implementation	
Building a Unified Database	What steps are required to develop the unified database from the initial data? What design considerations are important with respect to systems hardware and software?
Extracting Program Beneficiary Lists	For each program being targeting by the NTS, given program eligibility criteria, which could include economic status, demographic or geographic characteristics, and other indicators, how will a list of beneficiaries be extracted? (The unified database is not a single list of beneficiaries for all programs.)
Socialization and Communication	Who will develop detailed and comprehensive guidelines on socialization of all program and targeting elements to all levels of stakeholders? What will these guidelines and associated activities look like? Who will conduct which activities at what levels?
Maintenance and Updating	
Complaints and Grievances Protocols	Through what channels can complaints be made, and who will receive and address them? What responses are possible for each type of complaint? Who will act as an independent body for arbitration or settlement?
Updating and Recertification Protocols	What household information can be updated? How frequently can this information be updated and households reassessed? How frequently should the entire registry be recertified?
Monitoring and Evaluation	How can fraud and duplication be monitored for in the registry? Who will conduct cross-checking of the registry with other agency lists, and how will this be done? Who will conduct operational spot checks, and evaluations of targeting outcomes?
Program Exit Strategies	Can recertification of the unified registry be aligned with program exit strategies?
Future Directions	
Payments Support	How might an NTS support an integration of program payment processes?
Evolution of Social Assistance Strategy	How is social assistance design and strategy likely to evolve? How might the NTS be required to support such a transition?

05

Designing a National Targeting System

Designing a National Targeting System includes two key considerations. Section 4 has discussed how an initial database could be constructed, and described the recent PPLS11 data collection. In addition to data collection, there are two further important design considerations. What are the targeting objectives of the system? What is the legal and institutional framework required to support such a system? This section looks at these two aspects of designing an NTS in further detail.

5.1 Review of Targeting Objectives and Systems Used by Different Programs

The targeting requirements of a particular social program are determined by its objectives, and the target population that is intended to benefit from the program. In developing countries in general, social assistance programs target the 'poor'. However, this can be defined in various ways, and certain programs target particular sub-categories of poor households or individuals. Some programs may be directed to the poor or extreme poor because governments want to support their incomes or provide better education for their children, while others might target non-economic deficiencies such as malnutrition. Others may be designed to protect some vulnerable or at-risk groups against certain events that may affect their standard of living during a crisis, such as illness or unemployment, or crop failure.

In addition, achieving the objectives of any particular program might require the use of several targeting instruments, which may involve individual or household targeting methods, group assessments (geographical or categorical), or a combination of individual or household and group assessment methods.[73]

73 The different methods are discussed in detail in Coady, Grosh and Hoddinott (2004), and their application in Indonesia in World Bank (2012a).

Consequently, it is critical to review the information requirements of the different programs and the targeting systems currently employed. To understand the breadth and depth of data requirements for a unified database, we must summarize all program targeting objectives and intended beneficiaries. Table 5.1 outlines the target populations of the main social assistance programs in Indonesia,[74] highlighting three possible categories of program objectives:

1. To benefit individuals and or households;
2. To benefit groups of people that reside in certain communities, sub-districts or districts in the territory;
3. To benefit certain individuals or households belonging to groups or residing in particular groups or areas.

In other countries, a wide range of programs and targeting objectives are serviced by National Targeting Systems. In Colombia, a National Targeting System (Sisben) has been used by at least 10 different institutions for more than 20 various programs. While the Sisben PMT score was used for initial selection criteria, additional eligibility criteria could also be added by programs depending on the programs' needs. For example, the Ministry of Education, which runs a program on fee waivers for basic education and conditional cash subsidy for secondary education in Bogotá, used age of student in addition to the Sisben score to define the eligible recipients. Meanwhile, the Ministry of Social Protection only used the Sisben score as the selection basis for beneficiaries of the Subsidized Health Insurance Program for the Poor. For further detail, see Table 5.2 and National Planning Agency (2008). The six main programs in Chile also use a National Targeting System (Ficha CAS), by applying the CAS PMT score and other different selection criteria. Programs such as housing subsidies for the extreme poor and poor, for example, used Individual CAS scores for programs offering subsidies to individual applicants plus other criteria, such as not owning a house, or prior savings. For collective applicants, aggregate CAS scores below a minimum threshold, plus other criteria, such as prior savings, assets, or bank financing, were used as eligibility criteria. Table 5.3 and Larranga (2003) provide more detail.

74 See World Bank (2012a) for detailed discussion of program targeting procedures and World Bank (2012d) for a comprehensive review of program design and impact.

It is critical to review the information requirements of the different programs and the targeting systems currently employed.

Table 5.1: Main Indonesian Social Assistance Programs and their Target Populations (2009)

	Poor	
	All	Certain categories
Programs directed to individuals or households		
Unconditional Cash Transfer (BLT)	✓	
Conditional Cash Transfer (PKH): poor households with children		✓
Health Insurance for the Poor (Jamkesmas)	✓	
Rice for the Poor (Raskin)	✓	
Assistance for the Disabled: poor households with disabled members		✓
Fee waivers in hospitals or schools	✓	
Programs directed to people in groups—communities, schools, villages, and others		
Early Childhood Development: households with small children in poor communities and villages		✓
School lunches: students in schools in poor areas		✓
Community Driven Development (PNPM-Mandiri): components to poor communities	✓	
Individuals and households in certain groups or areas		
Public Works (potential program): people in poor areas, or those experiencing an unemployment shock		✓
Conditional Cash Transfer (PKH): households with children in poor areas		✓

The Colombian National Targeting System (Sisben) is used to target a range of programs...

Table 5.2: Colombia: Programs and Institutions using the National Targeting System (Sisben)

Institution	Programs	Targeting criteria
Family Welfare Institute (ICBF)	Programs Mother-child nutrition program ECD — community based program Day care programs Care for disable children Breakfast program for infants (Type 1 and 2) School feeding program National feeding program for elderly poor Program to support dispersed rural populations	Main targeting criteria: Sisben score plus category
Accion Social (Social Program under the President's Office)	Conditional Cash Transfer Program (Familias en Accion) Re-training of labor force (Reconversión socio laboral)	Sisben score plus eligibility criteria for families and individuals
Ministry of Social Protection	Social Protection Program for the Elderly (PPSAM) Solidarity Pension Fund – Subsistence Account Subsidized Health Insurance Program for the Poor	Main criteria: Sisben score
Ministry of Agriculture and Rural Development	Housing Subsidy for the Poor (VIS) Rural	Main criteria: Sisben score
Ministry of Environment, Housing and Regional Development	Cash Subsidy for Housing of Poor (formal and informal sector) –urban/rural	Sisben score plus income and other family characteristics
Institution	**Programs**	**Targeting criteria**
National Training Program (SENA)	Youth training program (Jóvenes en Acción) Rural Youth Training Program (Programa Jóvenes Rurales)	Sisben score plus age characteristics
Colombia Student Loan Program (ICETEX)	ACCES Program	Sisben score plus economic classification of area of residence
Ministry of Education	Fee waivers for basic education Subsidized school feeding, transport and school supplies Conditional cash subsidy for secondary education in Bogotá	Sisben score plus age of student.
States and municipalities	Fee waivers (reductions) in hospitals, health clinics School feeding Other local social welfare programs	Sisben score, other criteria such as age
Integrated Social Program (Red Juntos)	Contains CCT program, health insurance, other programs	Sisben score plus family eligibility criteria.

Source: National Planning Agency (Departamento Nacional de Planeación) 2008

...as does the Chilean National Targeting System (Ficha CAS).

Table 5.3: Chile: Main Programs Using the National Targeting System (Ficha CAS)

Program	Targeting criteria
Assistance pension for elderly or disabled not covered by formal pension system	CAS score plus elderly over 65 years of age or disabled over 18 years of age. Income per capita lower than pension
Family cash assistance program (SUF) for the poor	CAS score plus children less than 18 years of age that attend school, 0-6 years of age attend health check- ups, no cash assistance for beneficiaries of social security system
Cash assistance for the poor to pay for water and sanitation services	CAS score, plus beneficiary needs to be current in payments, could last for three years. Late in more than three payments leads to suspension.
Day care program (Program Integra)	CAS score or low income families, plus preference given children aged 3 months to 5 years of working, in-training, adolescent or unemployed (active) mothers
Housing subsidy programs for the extreme poor and poor	Individual CAS scores for programs offering subsidies to individual applicants plus other criteria, such as not owning a house, or some prior savings. For collective applicants, aggregate CAS score below a minimum, plus other criteria such as prior savings, owning a lot, or financing from bank.
Chile Solidario program	Integrated social program for the extreme poor. Initially used CAS score to select beneficiaries. Later on, Ficha CAS was replaced by family score card to select beneficiaries.

Source: Larranaga (2003)

5.2 Legal and Institutional Framework

Developing an NTS requires coordination and agreement among key parties. Critical in the practical operation of the NTS are the legal and institutional frameworks governing the system. This includes detailing the rationale for introducing the targeting system; establishing the general target populations of the system; clearly determining the agency(s) in charge of system design, organization and implementation; determining which programs will use the targeting system to identify their beneficiaries, and the responsibilities of those programs (data sharing arrangements); and establishing how often the system will need to be reviewed and updated, and how it will be funded. Finalizing these issues may well require new regulations or decrees. Moreover, a Program Management Unit (PMU) will need to be established to support the NTS. These issues are examined in this sub-section.

Legal Arrangements and Governance

A national targeting system needs to be supported by clear and formal rules and regulations. An NTS needs to be established with a solid legal basis, in order to clearly legitimize the NTS as the main means of targeting social assistance programs. Without a proper legal mandate, program implementing agencies may be reluctant to use the NTS on the basis of informal rules and agreements. Such a mandate can come from the rules governing the programs themselves, from the targeting system's legal mandate, or both.

A legal mandate in the form of a presidential decree or order offers a more flexible legal basis than a law. Targeting instruments and methodologies are likely to evolve over time. Consequently, an NTS is introduced in most countries through presidential decrees, cabinet documents, executive orders, or the like, rather than by enacting laws or constitutional mandates. While this may make the NTS vulnerable to political changes, it gives it greater flexibility to incorporate changes in methodologies or data sources as an NTS inevitably evolves.

The legal regulations for an NTS usually specify the rationale for the system, target groups, programs to be targeted, and frequency of review and updating. First, the regulations articulate the rationale for introducing the targeting system, a policy statement about the decision to direct specific social programs to the poor or other vulnerable groups. Second, they establish the general target populations of the targeting system, whether specific groups, people living in certain areas, people in certain categories, or other groups that are to benefit from social programs. Third, they identify the programs that will use the targeting system to determine their beneficiaries, and the responsibilities of those programs, including the main protocols to be followed, and responsibilities for feedback and safeguarding shared information. Finally, they also establish how often the system should be reviewed and updated.

Legal regulations also identify the institutional arrangements, such as which agencies will design and implement the system, as well as how the system will be funded. The regulations should clearly determine the agency(s) that will be charged with the design, organization and implementation of the targeting system. In some countries, such as Chile, Colombia and Brazil, the system design (targeting instruments and methodologies for data collection and quality control) is done by a central government agency, such as the National Planning Agency or Ministry of Social Development, while data collection is done by local agencies or governments. In other countries, such as the Philippines and Mexico, the design is done by a central agency such as the Social Welfare and Development Ministry, and data collection is performed by the regional offices of the same agency. The advantages of a centralized implementation approach include that a central agency can install better quality control measures (for instance, a single data entry application with validation routines) and follow uniform procedures, and is generally less vulnerable to local political interference and possible manipulation during the data collection process, whether by enumerator or household respondents.[75] In addition to identifying agency roles, the regulations should also specify how the system will be funded, including initial set-up and roll-out, maintenance and recertification. In countries such as Colombia and Chile, expenditures are shared between the central and local governments, since the main users of the system are central government agencies and local programs.[76]

Previously, Statistics Indonesia has conducted many of the targeting functions in Indonesia. In the past, Statistics Indonesia has performed many of the PMT targeting roles in Indonesia, from data collection to beneficiary selection to updating (see Box 4.2 on the evolving role of Statistics Indonesia in targeting in Indonesia). However, PMT targeting functions are rarely performed by national statistical agencies elsewhere in the world; generally they are handled by the Ministries of Planning or Welfare (Coady, Grosh and Hoddinott 2004). The key danger of having the statistical agency determine program beneficiaries is that of reputational risk. If households believe that the agency plays a role in selecting program beneficiaries, then they may be more likely to lie or try and manipulate unrelated surveys and censuses, thinking this increases their chance of receiving assistance, and thus undermining the primary role of the agency.

The National Team for Accelerating Poverty Reduction has taken the main coordinating role as the initial stages of an NTS have begun in Indonesia. The role of Statistics Indonesia in targeting has been reducing over time, and as an NTS is developed in Indonesia, long-term decisions will need to be made over which institutions play primary roles in data collection, data updating, recertification, and beneficiary selection. The National Team for Accelerating Poverty Reduction (TNP2K) Executive Secretariat, in the Vice President's Office, is currently playing a coordinating role, as well as constructing PMT scores and extracting initial program beneficiary lists in 2012, in addition to designing the other NTS components, such as updating, coordinating with line ministries, addressing complaints and grievances, and monitoring and evaluation (see Box 5.1).

75 A discussion of advantages and disadvantages of centralized versus the decentralized approach to implementation of data collection can be found in Castaneda and Lindert *et* al. (2005).

76 In Colombia, for instance, the central government finances up to 70% of the cost of data collection. This is justified on the grounds that large national programs such as the Conditional Cash Transfer program (*Familias en Accion*), the Subsidized Health Insurance program, and the Family Welfare Institute (ICBF) are the main users of the system (www.dnp.gov.co/sisben).

Box 5.1: The National Team for Accelerating Poverty Reduction is currently performing a coordination role as an NTS begins to be developed in Indonesia.

Problems related to the lack of coordination in the design and implementation of national poverty reduction programs have undermined the effectiveness of the government's efforts to reduce poverty and vulnerability. To address these problems, President Susilo Bambang Yudhoyono established the National Team for the Acceleration of Poverty Reduction (*Tim Nasional Percepatan Penaggulangan Kemiskinan*, TNP2K) in 2010. The cabinet-level team is led by Vice President Boediono and includes representatives from government agencies responsible for the planning, financing and implementation of poverty programs.

To support the National Team, the President also established a secretariat that is housed in the Office of the Vice-President. The secretariat is responsible for drafting policies and programs, establishing a national targeting system, and integrating monitoring and evaluation activities. Its structure includes six working groups that were created to function as internal think tanks focusing on the following components:

- Cluster One: household-based social assistance programs, with separate stand-alone working groups focusing exclusively on health fee waivers and insurance for the poor.
- Cluster Two: community-based poverty reduction programs, including the National Community Empowerment Program (PNPM-Mandiri).
- Cluster Three: programs that stimulate the creation of work opportunities for the poor and vulnerable by providing support to enterprises and (micro-) private sector entrepreneurs.
- Monitoring & Evaluation: providing technical assistance to implementing agencies, and integrating M&E inputs that can be used by the National Team to track performance.
- Targeting: establishing and housing a national targeting system, featuring a national registry, as outlined in the medium-term development plan and subsequent presidential instructions. The working group will also responsible for providing technical assistance to implementing agencies to improve program targeting.

The mandate of the National Team and its secretariat extends for the full duration of the current administration – until the end of 2014. While TNP2K systems, such as the national targeting system, will be established during this timeframe, it remains to be clarified where these functions will be housed following national elections in 2014.

The long-term NTS institutional arrangements in Indonesia need to be determined in the next couple of years. Currently, TNP2K has both the coordination and implementational role for the NTS. Whether this remains the case in the long-term is a critical policy question which must be resolved in Indonesia. Statistics Indonesia has been performing data collection, which is contrary to international norms; should they continue to do so, and if not, which agency should? Furthermore, who would provide oversight and governance for the NTS? Finally, what would the role of local governments, agencies and communities be? Some local agencies actually prefer a centralized system, as an agency conducting its own targeting often faces substantial pressure from people who want to be included, especially for programs run at the local level.[77] However, any arrangement will require a strong and capable program management unit, oversight from a steering committee, and assistance from a technical advisory committee, discussed in the next sub-section.

There are three main possibilities for Indonesia. Targeting responsibility could remain with TNP2K, move to a more permanent central agency, or, perhaps optimally, be performed by an independent institution. Three institutional frameworks are apparent. As discussed, TNP2K is currently developing the initial unified database from the PPLS11 collected by Statistics Indonesia, as well as conducting socialization with central and line ministries. One option for the longer term is for TNP2K to continue developing a targeting division, with the technical capacity to plan data collections, beneficiary scoring and identification, registry updating and recertification, and monitoring and evaluation activities, as well as capacity to oversee complaints and grievances. The advantage of this is that it builds upon the capacity in TNP2K currently being developed. However, it is unclear how permanent TNP2K is as an agency, and what its role would be under the new Indonesian government to be elected in 2014. There is a risk of losing the institutional knowledge and capacity in the future. An alternative is to move the targeting functions to a more permanent ministry, such as the National Planning and Development Agency (Bappenas), the Coordinating Ministry of Social Welfare (Kemenkokesra), or Kemensos, a department which is responsible for targeting in many other countries. These institutions currently lack the capacity to conduct targeting in Indonesia, but their permanent nature means that capacity might be built over time. However, the frequent movement of civil servants in and out of different divisions means that

77 For example, in Colombia many mayors prefer to acknowledge that they have only a limited role, or no role at all, in determining the final list of beneficiaries for certain programs, while at the same time proclaiming that they have been instrumental to bringing the program to their territory (Castaneda and Fernandez 2003).

such capacity might also be easily lost, and that the targeting function could be run by a series of officials without much experience or knowledge of this relatively technical area. Finally, and perhaps preferably, targeting functions could be moved to an independent institution under the supervision of a high level oversight committee, possibly housed in a central ministry such as Bappenas. This would enable capacity to be built in a more lasting fashion, help insulate targeting from political pressures, but retain clear lines of accountability. Transition to this arrangement could occur over the next three years, with TNP2K continuing to design and implement the NTS, build capacity and experience, and extract beneficiary lists. The targeting division within TNP2K could then be established as an independent institution, with accountability either to the Vice President's Office or cabinet, or to an oversight committee comprising top officials from agencies such as TNP2K, Bappenas, Kemenkokesra, program implementing line ministries, and Statistics Indonesia.

A related question concerns who will collect data, both for updating and recertification purposes, in the long term. Statistics Indonesia is currently the only agency with sufficient capacity to do so, but may suffer reputation risk over time. The dangers of Statistics Indonesia continuing to perform the data collection role for the National Targeting System were discussed in Section 4 and earlier in this section. However, there is currently no other agency with the capacity to conduct the large-scale survey work that recertification of the registry implies. In the short term, Statistics Indonesia is likely to continue this role. In the long term, if another agency were to adopt the function, a significant investment in capacity building would be required. One possible long term candidate is Kemensos, which has local offices in every district. Experience in data collection from households could be built up over time by having the agency participate in the annual or semi-annual updating (see Section 7), so that skills could be developed on a smaller scale before recertification of the entire registry. In addition, it would be appropriate for the data updating function to be performed by the same agency overseeing the complaints and grievances process at the local level, another function which Kemensos might perform. However, the investment in developing this function in an agency other than Statistics Indonesia would be substantial, and the possibility of mistakes initially are significant. Failures in both updating and complaints and grievances would threaten the effectiveness of the NTS considerably. Table 5.4 summarizes a possible institutional arrangement for Indonesia, governing all aspects of an NTS.

The institutional framework for a National Targeting System in Indonesia might evolve over time

Table 5.4: Possible NTS institutional Framework

Initial Design and Operations: 2011-2012	
Function	**Agency(s)**
Identification of targeting objectives	Targeting Unit and Statistics Indonesia, in consultation with line ministries of participating programs.
Initial legal mandate	Already done by Presidential Instruction (INPRES).
Design of initial data collection	Targeting Unit and Statistics Indonesia. Completed.
Initial data collection	Statistics Indonesia. Completed.
Compile initial database	Targeting Unit
Develop MIS	Targeting Unit
Develop data sharing arrangements	Targeting Unit
Extract initial beneficiary lists	Targeting Unit, in consultation with line ministries of participating programs.
Develop complaints and grievances handling protocols	Targeting Unit, in consultation with line ministries of participating programs.
Develop periodic updating protocols	Targeting Unit, in consultation with line ministries of participating programs.
Develop monitoring and evaluation system	Targeting Unit

Governance: 2013 onwards	
Function	**Agency(s)**
Final legal mandate for institutionalization of NTS	Presidential Instruction. Should include establishment of permanent Targeting Program Management Unit (PMU). PMU to be an independent unit, reporting to NTS Steering Committee, and advised by NTS Technical Advisory Committee.
Oversight	NTS Steering Committee, consisting of TNP2K, Bappenas, participating line ministries, Coordinating Ministries for Economics and Welfare. Committee role is to ensure NTS objectives are met, including: maintenance of a functional, objective, and transparent NTS; data sharing arrangements with program implementing agencies; and recertification schedules and budgets.
Technical Assistance	NTS Technical Advisory Committee, consisting of TNP2K, Statistics Indonesia, and international aid agencies. Committee role is to provide technical advice and oversight on the targeting methods and methodologies used, and on data gathering, treatment and analysis, and data management.

A possible long-term institutional framework for a National Targeting System in Indonesia (cont.)

Operations and Maintenance: 2013 onwards	
Function	**Agency(s)**
Handling of complaints and grievances	Independent Targeting PMU, established from TNP2K Targeting Division. Participating line ministries to facilitate reporting of complaints. Supported by NTS Technical Committee.
Periodic updating of beneficiary data	Statistics Indonesia, in transition to another agency (possibly Kemensos).
Implementing data sharing between NTS and program MIS	Independent Targeting PMU.
Develop monitoring and evaluation system	Independent Targeting PMU, supported by NTS Technical Committee.
Conducting database recertification	Agency responsible for periodic updating. This may still be Statistics Indonesia in 2014, but transitioning to another agency over time (possibly Kemensos).
Coordinating program exit strategies with NTS	Independent Targeting PMU, in coordination with participating line ministries.
Coordinating with payments support	Independent Targeting PMU, in coordination with participating line ministries.

Program Management Unit and Institutional Capacity Building

A national targeting system requires a full time Program Management Unit to support it. Developing and managing an NTS requires high technical capacity, staff, financial resources, and a sophisticated MIS infrastructure. A Program Management Unit (PMU) is therefore required, which is fully dedicated to the establishment and updating of the beneficiary database, conducting socialization to all relevant stakeholders, supervising the sharing of data and beneficiary listings with partner agencies, and dealing with complaints, grievances and oversight agencies. A typical Targeting PMU is led by a national Project Director (PD) and organized around six core areas: (i) planning, monitoring and evaluation; (ii) budgeting and financial management; (iii) social marketing and socialization; (iv) operations and data sharing; (v) complaints and grievance redress system; (vi) IT hardware and software, and communications. An organization chart is presented in Figure 5.1, and each of these core functions is discussed in turn.

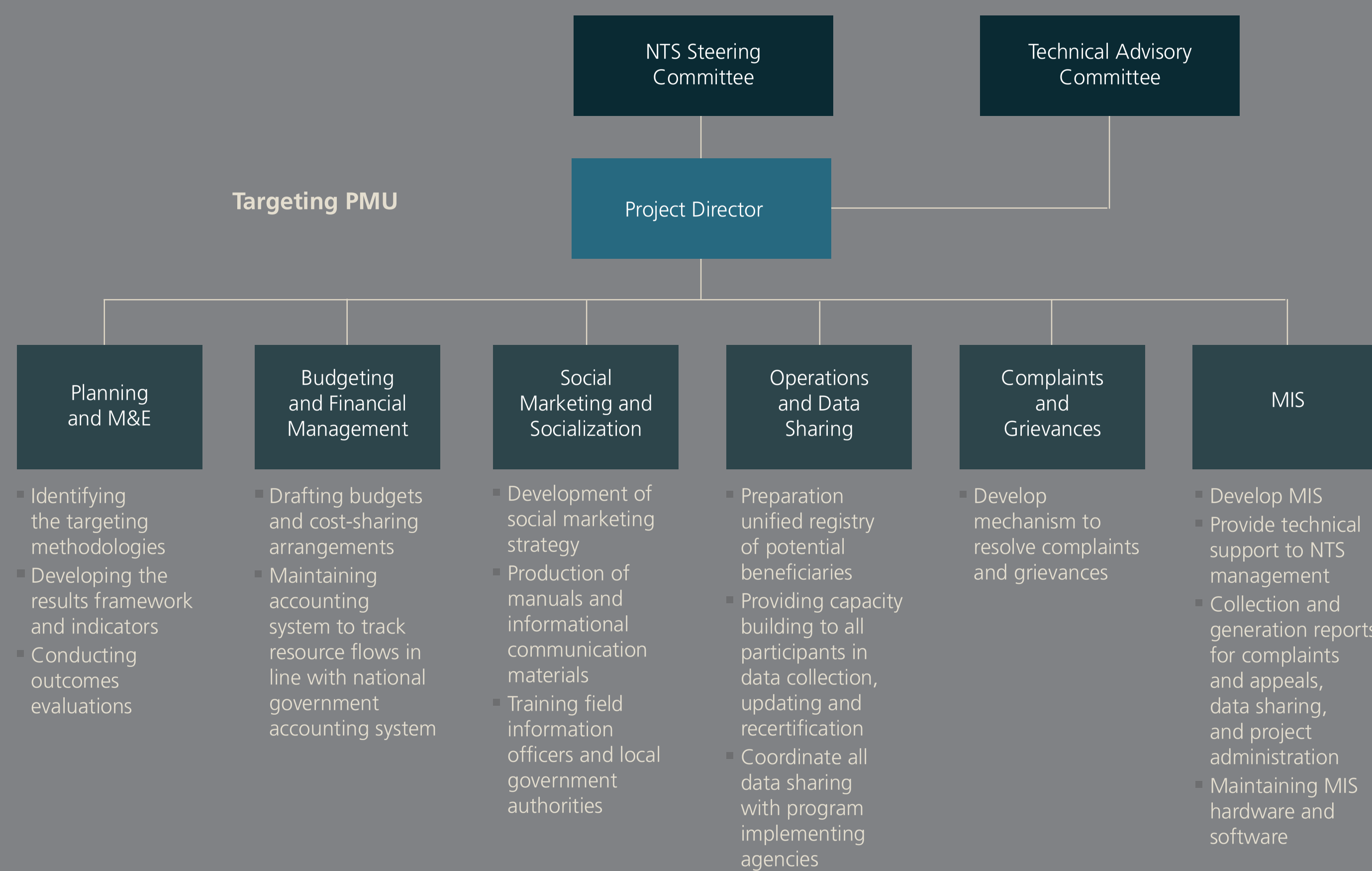
Planning, monitoring and evaluation of the NTS would be conducted by the PMU. One section of the PMU would be responsible for all planning activities related to establishing the national database, data sharing with partner agencies, and monitoring and evaluation. Responsibilities include identifying the targeting methodologies and implementation procedures to be followed, developing the results framework, follow-up indicators, and outcomes to be monitored regularly (using contractors or independent agencies), and planning and conducting concurrent and ex-post evaluations.

All financing aspects of the NTS are performed by the budget and financial section of the PMU. Responsibilities include drafting budget proposals and cost-sharing arrangements to meet the costs (initial and recurrent) of building and maintaining the national targeting system and database. The section would develop, operate, and maintain a budgeting and accounting control system to track project budgets and resource flows in line with the national government accounting system.

Another section would develop and execute the targeting system's social marketing and socialization strategy. The socialization and communications section is in charge of the design and production of manuals and instructional kits, and information, education and communication materials for the conduct of social marketing activities, in addition to the overall social marketing strategy. This section should also train field office information officers and local government authorities to ensure that key messages reach their intended audiences, in order to gain and maintain their support.

A National Targeting System requires a full time Program Management Unit to support it, revolving around six core functions, and led by a Project Director.

Figure 5.1: Organizational Chart of Targeting Program Management Unit.



The operations and data sharing functions is performed by another PMU section, which implements and coordinates all the activities related to data collection, processing and analysis, as well as data sharing with user agencies. Key among the responsibilities of the operations and data section are supervising the preparation of the final unified registry of potential beneficiaries of social assistance programs, including providing capacity building activities to all participants in the data collection, updating and recertification efforts. The section will coordinate all data sharing with program implementing agencies, in close coordination with the MIS function. It will also develop a responsive and transparent mechanism to resolve complaints and grievances relating to the implementation of the national targeting system, most importantly for households that were not assessed during the initial enumeration.

The PMU's MIS section would design and support the necessary information systems required by the targeting system. A well-designed and developed MIS is critical to the effective operation of an NTS. A separate MIS unit within the PMU would be responsible for developing this system. They would also provide technical support to NTS management and administration functions. This includes the collection and automated generation of reliable data, and developing and applying processes for including poor households in the database, handling complaints and appeals, data sharing, and project administration. The section will also be responsible for maintaining the MIS hardware and software.

The NTS and PMU also require a strong oversight and control system. The formal creation of two committees external to the Targeting PMU are required to ensure proper oversight and governance of the system. First, an NTS Steering Committee should be created by ministerial order or similar means, to ensure that the objectives of the NTS are met. Specifically, the committee would oversee the PMU's major functions, including: completion of the initial database of potential beneficiaries to be included in the NTS; maintenance of a functional, objective, and transparent NTS; data sharing arrangements with program implementing agencies; and recertification schedules and budgets. Members of the Steering Committee could include technical representatives of the different partner agencies using the national database of beneficiaries, such as Jamkesmas, PKH, scholarships, and other programs. In addition, a Technical Advisory Committee is required to provide technical advice and oversight on the targeting methods and methodologies used. This group could be composed of representatives from Statistics Indonesia, universities and other centers of technical excellence, and international aid organizations. The PMU would draw from the technical expertise and experience of these agencies in data gathering, treatment and analysis, and data management.

Data Sharing Arrangements

Data sharing arrangements to govern the unified registry must also be developed. Data sharing needs to be governed by specific rules and obligations, such as those of the PMU to provide updated and accessible high quality and reliable information on prospective beneficiaries, and those of partner agencies to use data only for the purposes agreed upon, in a secure fashion, reporting back on the beneficiaries finally selected, and channeling targeting complaints from beneficiaries. In addition, agreement on common household and individual IDs, or at least name and address formats, is essential if the unified registry is to be cross-checked with other lists.

These arrangements need to be governed by specific rules and obligations. The main responsibilities of the agency managing the single targeting database are to: (i) provide high quality and reliable information on the prospective beneficiary targets of the different programs; (ii) provide clean and updated data; and (iii) provide easy access, whether direct over the internet to secured data, or through direct electronic provision of lists extracted by the targeting agency according to program-defined eligibility criteria. In turn, the main responsibilities of the partner agencies are to: (i) use data only for the purposes agreed upon under the signed Memorandum of Agreement; (ii) secure information that could be confidential; (iii) provide feedback to the targeting agency on the actual use of the data by reporting back which beneficiaries were finally selected for the programs; and (iv) properly channel any complaints and grievances regarding targeting or related issues from the user agency or beneficiaries.

The database can also be used to cross-check beneficiaries of existing programs, but this can be challenging. This occurs for existing programs with an objective of establishing the extent of leakage in those programs. There are several challenges when conducting cross-checking, due to several factors including incompatibility of databases, information not being in an electronic form, or without a common identification number to match efficiently. In many cases the only information common in the databases is the name of beneficiaries, which makes it very hard to cross-check the data properly.

In certain countries, the NTS data are shared with partner agencies by internet portal, with specific rules and procedures for feedback from the institutions about the database. One possibility is to create a web portal for data sharing with partner agencies. The shared database should be limited to a few variables that are common to many programs, taking into consideration that in many countries personal data are protected and cannot be disseminated. Should a specific program need additional information, such as the complete family roster, it could be requested from the targeting system. The shared dataset can be updated periodically, depending on the targeting system's updates and on-demand application rules and procedures. Clearly security of such a portal is critical. In addition, should a person or household in the database be selected for a particular program, that information should be reported back to the NTS PMU. This ensures the national database will be a listing of beneficiaries and the programs in which they are participating. This is done in the *Chile Solidatio* program, which has a database of benefits and people receiving those benefits.[78] In Argentina, the Social Security Agency (ANSES) provides cross-checks of databases for all social programs being used by an individual.

In principle it is possible to build incentives for reporting the use of the shared datasets. For instance, institutions promptly and properly reporting back the use of the data can be given priority for easier access to additional data. All data transactions should be kept in the audit logs of the Web portal for follow up and enforcing data sharing rules and procedures.

78 www.mideplan.gov.ch/chilesolidario

06

Implementing a National Targeting System

Three key considerations in implementing an NTS are examined in this section. The three main aspects of implementing an NTS are building a unified database, extracting program beneficiary lists, and conducting socialization and communications activities. This section focuses on the extraction of beneficiary lists. However, the other two aspects are also briefly addressed.

6.1 Building a Unified Database

Once initial data collection is complete, an MIS system containing the unified database must be developed. Selecting hardware and software to manage the database for a national targeting system is a significant issue. The choice will depend on the size of the database, the nature of the system to be developed (whether static or transactional), and the institutional capacity to develop and maintain the system. In addition to hardware and software, a unique identifier for individuals and households is desirable. This is examined later in this section.

Hardware requirements are becoming increasingly high. Most modern targeting systems, whether built with existing databases or newly collected stand-alone systems, require a highly robust database platform, on-line capabilities, and an ease of use for partner agencies. The government agency in charge of the system can either host the database on its own servers or buy hosting services from a number of local or international private providers.

The development of a management information system (MIS) is a major software task. An MIS to support the NTS can be developed in two ways. It can be outsourced to a private provider, or developed in-house with qualified system analysts and programmers. Neither alternative is straightforward. Outsourcing can fail if there is little coordination

between the firm and end users in developing the business process required by the system. However, developing an MIS internally requires highly-trained system analysts and programmers, which public agencies in developing countries can find difficult to hire, given often competitive private sector salaries.

A key obstacle in building a national registry is the absence of a single national identification number system. Without unique individual or household identification, it is difficult to merge databases from different programs, compile beneficiary lists, search for duplicates, and cross-databases with administrative databases such as tax, vehicle and property records. Even in some countries with a national identification number, many poor people, migrants and undocumented workers do not have official ID cards due to lack of birth certificates, residence papers or other legal documents.

In the absence of unique identification systems, targeting initiatives often resort to creating their own approach in parallel to other initiatives. As civil registration and identification processes have evolved, more and more purpose-specific identifiers have been issued by authorities at multiple levels of government. One of the most common approaches is to create an identification from a combination of geographic location (province, municipality, neighborhood) and the names and birth dates of people in the database. Ultimately, this has resulted in a complicated situation wherein each citizen has, and has to maintain, numerous registrations, numbers and cards. The associated data are spread across the government and across the country. As a result, many of the data may be incorrect, duplicated, or incomplete. By registering in different locations, some individuals have been able to register multiple times undetected.

Indonesia's national identity cards face many challenges and, in the current form, cannot be used for a social assistance targeting system. A form of individual (KTP) and household ID exists in Indonesia. However, in practice people may hold more than one, be registered under the same name in different locations, and sometimes in different names. Moreover, not all people hold a KTP, which is not a legal requirement. Poor people in particular often do not have identity cards, as photographs must be purchased to include with the card. Finally, registering a KTP in a new location can be difficult, meaning migrant workers are often not eligible for social assistance even when they are poor.

To address these problems, Indonesia launched an initiative to build a national identity database that is still in the process of being created. In 1990 it was decided to build a National Population Information System that involved the computerization of population data on a nationwide basis. Each district (*kabupaten*) and city (*kota*) was to build its own population database that would be consolidated at the national level. Each district and city, however, developed systems using different software platforms, database tools, and even data structures, which made consolidation of the data into a single database extremely difficult. In 2003, the government launched a new Population Administration Information System (SIAK) that aimed to build a national population database (albeit distributed) using a single application with a single data structure based on a single ID number using a new format. Applications and servers were issued to each local government to carry out the data collection. The data conversion, consolidation, and validation effort continues to this day. The implementation of the application, however, does not necessarily mean the databases in those locations are complete and correct. Nor does it mean that all the people in any given district or city are included.

The Government of Indonesia is now converting to electronic identity cards (e-ID). With the introduction of digital ID card technology, it was decided (and mandated by a Presidential Decree in 2010) that all current national ID cards should be converted to e-ID cards by 2012. The 'e-KTP project' has emerged as a national flagship initiative and momentum continues to grow. The Ministry of Home Affairs (Kemdagri) has the primary responsibility for the initiative, supported by a technical advisory committee made up of government and academic technology specialists. The SIAK application and database will be the foundation for the e-KTP system. All citizens over the age of 17 holding KTP will present themselves to the district population registration offices where they will turn in their cards and their biometric data will be collected. The biometric data for each individual will be transmitted and consolidated centrally where it will be matched with the same individual's data in the SIAK database. Digital ID cards will then be created (centrally) for each individual and returned to the sub-district offices for issuance the individuals.

Indonesia's smart card strategy needs to be re-considered if it is to be used for other purposes, avoiding the expensive creation of parallel identification systems. The main purpose of the e-KTP is to prepare for the next round of national elections. The instructions from the President call for the process to be completed in time for a list of eligible voters to be delivered to the Electoral Commission by mid-2013 for the 2014 general election. Extending the proposed e-KTP to other purposes, such as the delivery of social assistance benefits, is difficult given the current project design. It has already been decided that the e-KTP will be contactless, single-purpose–identity only; with only 8kb of memory it is unlikely that they can also be used for other purposes such as social assistance or financial inclusion programs. In addition, there is no support for interfaces between the population database and a number of other applications (migrant worker management, provincial social services management) that would be needed for a multi-purpose identity card. In re-designing the strategy, Indonesia could optimize the unique electronic identification in order to facilitate the delivery of targeted social services. Box 6.1 discusses how this has been done in Pakistan and India.

Box 6.1: Much can be learnt from international best practices in creating unique identification systems.

Introducing a unique identification number system is a complex process that involves not only technical aspects but also important political considerations. Some countries – including Pakistan and, to a lesser extent, India – are implementing strategies to provide national identification numbers to their citizens. Modern alternatives such as collecting biometric information are being gradually included in some programs to identify beneficiaries. Other countries, such as the United States, have resisted the idea.

Pakistan has developed a sophisticated unique identification system. The National Database and Registration Authority (NADRA) has, to date, registered over 116 million citizens and has issued 85 million smart identity cards that include biometric information. The smart card initiative has been linked to the country's poverty database, allowing them to adopt a tiered approach to subsidy management where poor households receive more subsidies than other households. Beyond social protection, the smart cards have been used effectively to provide a broad range of other services including: health and education, financial inclusion strategies, and loyalty programs. The cards work in conjunction with mobile phone applications to also improve the delivery of financial services. Robust biometric verification and eligibility verification procedures have also helped to reduce fraud and save public funds.

India is following suit and in 2010 launched the Aadhaar program that aims to establish unique IDs for its 1.2 billion citizens. The smart cards will store basic demographic and biometric information in a central unique ID database, which can be used by service providers to authenticate identities on-line and in real time. Aadhaar's soft infrastructure provides a platform for multiple applications that can also be linked to bank accounts and mobile phones. This will allow the system to channel cash entitlements (such as scholarships and pensions) through unique ID-enabled bank accounts. This may not only improve the effectiveness of social assistance delivery, but also lower the transaction costs for the delivery of basic financial services.

6.2 Extracting Program Beneficiary Lists from a National Targeting System

The unified registry is not a single list of beneficiaries for all programs. Different targeting objectives will require different selection methods. Once a unified registry has been collected, this does not automatically determine beneficiaries for all programs. The unified registry is intended as a single repository of consistent, high quality data on potential beneficiaries that can be used, not used, or augmented by different programs, depending their targeting needs. The initial PPLS11 data collection covered around 40 percent of Indonesian households. It includes individual, household and location characteristics for each household which can be used to estimate poverty status, as well as demographic information on household members, such as age, sex, pregnancy status, and school enrolment. Using these data, initial program beneficiary lists can be extracted from the resulting unified registry. Since different programs may have different eligibility criteria and coverage levels, each list will need to be extracted separately. For example, Jamkesmas is targeted at the all members of poor and near-poor households, or around 76 million people living in 19 million households. In contrast, PKH is targeted at the poorest 3 million households which have pregnant women, children aged 0 to 5 years old, or school-aged children. Targeting also needs to allow for changing household circumstances, especially for those experiencing a shock or entering poverty. The remainder of this section examines how beneficiary lists can be selected using different approaches for different targeting objectives, including generating different lists from the unified registry, modifying and updating these lists with additional methods, or selecting beneficiaries without using the registry at all. We conclude this section by suggesting which approaches are most suited to different types of programs and targeting objectives.

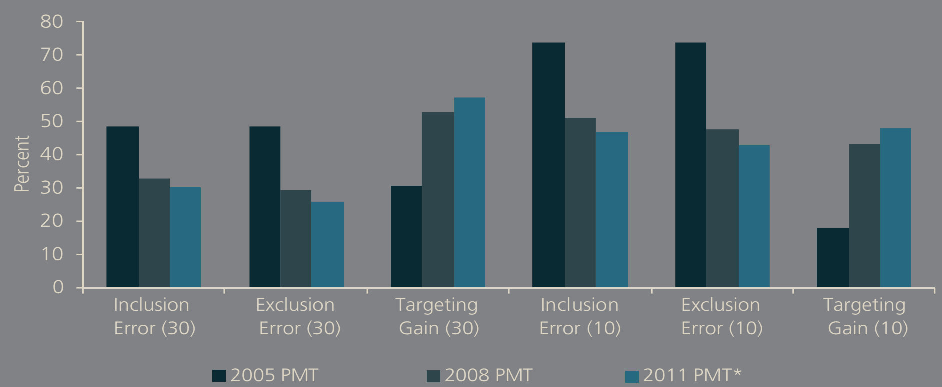
Constructing Beneficiary Scores from the Unified Registry

From the unified registry, different lists can be generated using different criteria and scoring methods. There are three ways in which the PMT information can be used to create different beneficiary lists. The first is the choice of variables, the second is the choice of scoring objective, and the third is how these scores are used to determine a beneficiary eligibility threshold (see Box 4.1 for an overview of the steps involved in implementing PMT). We look at each of these in turn, beginning with the most common, targeting low per capita consumption households (low daily living standards).

The PMT specification used in 2008 is already a relatively accurate model for selecting low consumption beneficiary households, although it can be improved incrementally through the use of additional variables. Statistics Indonesia introduced a considerably more sophisticated PMT approach in 2008, compared to 2005, collecting a broader range of household and community indicators, then scoring them with weights from a consumption regression, following international best practice. As Figure 6.1 shows, targeting outcomes using the 2008 PMT are significantly improved over the 2005 PMT, with over 20 percentage point reductions in inclusion and exclusion errors for simulated programs targeted at either the near-poor and below, or just the very poor. However, small incremental gains are possible by adding new asset variables included in the latest national socio-economic survey (Susenas) from which consumption regression scores are obtained.[79]

The PMT used in 2008 for PPLS08 is a significant improvement on that used in 2005. However, small improvements can be made.

Figure 6.1: Targeting Outcomes of Different Proxy Means Test Specifications when Targeting Low Consumption



Sources: Susenas, World Bank calculations.
Notes: Three different PMT specifications and scoring systems were applied to the entire Susenas survey. "2005 PMT" uses the PSE05 PMT of 14 indicators and statistical but non-consumption regression scoring. "2008 PMT" uses the PPLS08 PMT of 49 indicators with consumption regression scoring. "2011 PMT*" does the same as 2008, but adds some additional variables available in Susenas 2010, including five new asset indicators. Each PMT score was used to target two different programs, one targeted at the poorest 30 percent (targeting outcomes indicated with (30)), and one targeted at the poorest 10 percent (targeting outcomes indicated with (10)).

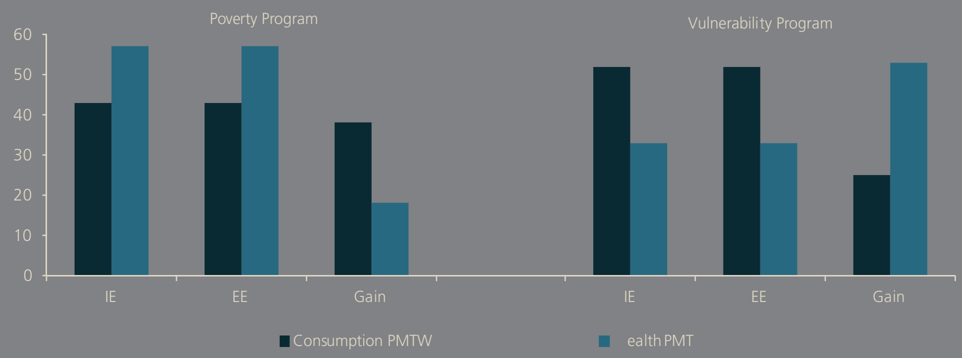
However, alternative PMT scores can be constructed for non-consumption based targeting objectives as well. The same variables can be used in PMT for different targeting objectives. In most countries PMT scoring weights come from regressing household income or consumption on the PMT indicators. However, if the targeting objective is not measured by daily living standards, but, say, economic vulnerability or malnutrition, it is possible to create alternative PMT scores using the same (or different) indicators. For example, if a program were targeting vulnerability of living standards rather than living standards themselves, then it might be more concerned about security of income and ability to weather shocks, than it would about consumption levels. Household wealth (the total value of assets such as livestock, vehicles, jewelry, appliances, and business equipment), for example, can be sold or borrowed against in case of a shock, and so reflects the ability to smooth consumption, rather than the level of consumption itself. Household wealth and household consumption are only moderately correlated, with many households having high levels of consumption but low levels

79 See Technical Annex 2 of this report and *Optimal Proxy Means Tests in Indonesia* (World Bank 2012b) for much more discussion on the most effective design and use of PMT in an Indonesian context.

of assets, and others having lower levels of consumption but more assets.[80] Using total household asset value as both program targeting objective and in the PMT scoring regression, we find inclusion and exclusion errors fall nearly 20 percentage points lower relative to a consumption PMT, and targeting gains double (Figure 6.2).[81]

When targeting poverty or low living standards, consumption-based PMTs have an advantage, but for vulnerability programs, targeting wealth may lead to better outcomes…

Figure 6.2: Targeting Outcomes for Poverty and Vulnerability Targeted Programs



Sources: IFLS and World Bank calculations.
Notes: "Consumption PMT" indicates PMT scoring coefficients were from per capita consumption regressed on PPLS08 specification. "Wealth PMT" indicates per capita wealth was the dependent variable. Wealth is the total value of all household assets, including farm and non-farm businesses. The poverty program is aimed at the poorest 30 percent of households by per capita consumption, while the vulnerability program is aimed at the poorest 30 percent of households by per capita wealth.

A particular PMT score can also be used in different ways to identify beneficiary eligibility. For example, an absolute scoring cut-off can be employed. Even for programs with the same targeting objective, such as low consumption, the PMT scores might be used in a different manner. There are two possible approaches. The first is to determine the strict PMT score threshold for eligibility. All households scoring below this level are admitted to the program, and all those above are excluded. The advantage of this method is that, subject to the PMT model accuracy, households with scores above the threshold are more likely to be non-target, so excluding them reduces inclusion error. The disadvantage is that if not all households in the country have been surveyed, programs may not identify as many households as they planned and budgeted for, creating operational and fiscal uncertainty.[82] In addition, the less accurate the model, the more likely that target households can have scores above the threshold and be excluded.

Alternatively, scores can be used to rank households, and the lowest ranked be used up to a set quota, regardless of score. The other approach involves ranking all households by their PMT score, and taking the lowest ranking households up until a program quota (which might be set with poverty maps or geographic targeting). This has the advantage of identifying the exact number of beneficiaries programs have budgeted and planned for. It may also mean that target households who scored just above a strict threshold and would have been excluded are correctly included. But it can also mean that non-target households get included. The more accurate the model, the more inclusion error is likely to be generated the higher above the strict threshold one goes. This can be mitigated by having a maximum score above which households cannot qualify, even if the quota has not been reached.[83]

80 See *Optimal Proxy Means Testing in Indonesia* (World Bank 2012b).

81 There are many other drivers of economic (in)security, which depends on source of income (type of industry, nature of employment or contract, exposure to prices and climate) and sources of recourse (wealth and savings, social connections and support). See *Optimal Proxy Means Tests in Indonesia* (World Bank 2012b). This paper also explores approaches to nutrition targeting (discussed also in Technical Annex 2 of this report).

82 In any case, even if a strict scoring threshold is used, it must be adjusted from the underlying consumption level it is based on, as it will not correspond directly to a real consumption value (see *Optimal Proxy Means Tests in Indonesia* (World Bank 2012b)).

83 Such a maximum score can be determined by simulations in the survey data. After constructing PMT scores for each household, we can plot the proportion of poor households excluded over an increasing PMT score. Policy makers need to decide what degree of exclusion error they are prepared to tolerate, and the related PMT score on the plot represents the maximum score.

The preferred approach will depend upon a program's targeting objectives and the nature of the benefits.[84] When a program, such as a conditional cash transfer, is targeted at the very poor, with the intention of helping those without other means invest in their children's human capital, then a strict threshold equivalent to a particular income or consumption level might be preferred. If insufficient households are identified, then it could be better to use other methods to identify the missing target households (such as community referrals or complaints and grievances) than to include households with scores indicating they most likely have higher consumption levels, and do not need the program's assistance. On the other hand, for a program targeting households who are poor or vulnerable to falling into poverty, such as a health insurance program, then a quota method may be better. As we have seen in Indonesia, many more households than simply the current poor are vulnerable to shocks and often find themselves in poverty in later periods. The value to these households of a safety net from a shock is similar to the value to a poor households, so ensuring the program covers as many households as possible is probably preferred.

Ultimately, lists developed solely from the unified registry will not be sufficient for all targeting needs. There is a need to allow households to enter program lists from other methods or an appeals process. Flexibility is required in order for households who were misevaluated initially, or whose circumstances have changed, to be added to a program beneficiary list. These additions could be through the use other targeting methods, which is examined next, or through either an individual appeals process or systematic updating and verifying of prospective beneficiaries, which is discussed in the Section 7.

Augmenting Beneficiary Scores with Other Targeting Methods

The unified registry can be used by program targeting in different ways. Lists based on the new PMT can be, altered or supplemented by additional targeting methods, such as categorical targeting. The PMT scores can be used directly by a program, such as an unconditional cash transfer program seeking to target the poorest 30 percent of households. However, a program may also combine these scores with other forms of targeting, such as categorical targeting. For example, a conditional cash transfer such as PKH requiring pregnant women to receive pre-natal healthcare, infants to attend primary health activities, and children to attend school, might extract a list of very poor households, but then follow-up checks are performed to confirm that these households are demographically eligible.[85]

Community-based targeting can also be used. Initial program sub-lists can be extracted from the registry, based on a household's PMT score and other data. However, these lists may simply form prospective beneficiary lists to be verified by the community, allowing them to update the lists for households whose circumstances have changed (discussed in Section 7), or who have been excluded due to model error. This approach may be particularly appealing if the data in the unified registry is out of date, if model accuracy is a problem, or if community satisfaction is important (see Section 2).

The registry scores can also support programs which use self-targeting. Alternatively, the registry may not be used to extract beneficiary lists, but be available in the case of a program that wishes to have potential beneficiaries apply. In this case, when a household applies to a program, the information in the registry can be used to determine or assist in the selection decision.

Targeting Outside of the Unified Registry

Targeting can still be done when appropriate without reference to the unified registry. There are programs which may target without using the unified registry at all. Programs better served by strict self-targeting are one example. A public works program which aims to provide short-term employment to households experiencing an idiosyncratic or more generalized labor market shock can set wages below the market level, so that only those who are truly under- or unemployed will seek to enter the program. In this case, the unified registry need not be used. This approach is generally considered effective from a targeting perspective (see Box 6.2), particularly in times of crisis when other targeting methods are not available quickly or are unlikely to be up-to-date.[86] Similarly, if very low quality rice was made available to anyone who wished to purchase it, or if birth assistance made free in public hospitals, then only households who cannot afford better quality are likely to participate. Of course, in these cases, given the large poor and vulnerable population in Indonesia, potential population coverage could be large. Finally, community driven development platforms could be used to target as well. In Indonesia, block grants are made available to sub-districts, where villages can propose

84 The two approaches are equivalent when all households have been surveyed and included in the registry. In this case, if the threshold and quota have been set consistently – that is, to identify the poorest X percent, or the poorest Y number of households which represent this X percent – then the same households will be selected under both methods, and with the same final total. See Optimal Proxy Means Tests in Indonesia (World Bank 2012b).

85 Even though this information is collected in the unified registry, circumstances may have changed.

86 For a more critical view of the targeting effectiveness, see Barrett and Clay (2003). McCord and Farrington (2008) is a brief overview of non-targeting issues with self-targeted public works programs.

particular projects of a menu of choices. Some of these projects could potentially include a social assistance or safety net component which communities could be allowed to target themselves.

Box 6.2: Self-targeting can be an effective targeting method for public works programs[87]

Self-targeting programs are open to all, but they are designed in such a way that they are used mainly by the poor. The non-poor choose, of their own accord, not to use them. The factors that contribute to this choice include private or transaction costs of participation. The time cost of public works programs is a classic form of self-targeting. To receive payment in cash or food, individuals must perform significant labor. Usually the jobs are organized offering full-day or nearly full-day employment on days worked, and in some cases offer a job for several weeks or months. Such full-time labor means that the workers must reduce the hours spent on other activities. Most workers would, in the absence of their public works job, be seeking and getting at least some employment, often as casual day labor or working on their own land or in their own micro-enterprise. Thus they would be generating some earnings in the absence of their public works jobs. The transaction costs to them of holding the public works job are the earnings foregone. Those who can earn more in outside jobs will not choose public works, and so select out.

Comparing targeting outcomes across different programs and different methods is very difficult (see Section 2.1), and a careful summary is not attempted here. However, an international survey of different methods by Coady, Grosh and Hoddinott (2004) suggests that public works programs with self-targeting have some of the better targeting outcomes.

When is self-targeting effective for public works programs? The critical factors are the wage paid relative to the market wage for such labor, and the distribution of wages in the economy. In Argentina's *Trabajar* program, the maximum wage paid was initially set at the minimum wage and subsequently lowered (to about the equivalent of the earnings of the lowest decile of the population). The program had one of the highest targeting scores of any program in the world. The Bolivian Emergency Social Fund, in contrast, paid the prevailing wage in the construction industry. Targeting was less progressive than for the Argentinean program, because the public works wage was not set lower than the reference wage (construction wages) and because the wrong reference wage was used (construction workers were not amongst the very poorest). If there are a lot of people earning near the public works wage, targeting will not be as good as it will be when the wage gradient is steeper. There is also an inherent contradiction between fine targeting and the level of benefit. In extremely poor settings where the market wage is already very low, it may be important to verify that the net wage (after taking into account the caloric expenditures required to do the job) from the public works job is high enough to meet welfare objectives.

Even in cases where the wage is set low enough to ensure that applicants for jobs are poor, if the program is not large enough relative to demand, then some other kind of rationing system will be needed, which could be informal (who knows the foreman) or formal (such as the lottery considered for Argentina's *Trabajar* program, the proxy means test used in Colombia's *Manos a la Obra,* or a community decision, as in the South Africa).

Matching Targeting Approaches to Different Programs

Different programs should target in different ways. We have looked at how different targeting scores can be constructed from the unified registry, and used directly to determine beneficiaries, or augmented with community-based approaches for example. We have also seen that not all programs are best suited to being targeted with the NTS. This section concludes by suggesting which approach is best for different program types and targeting objectives.

Programs designed to alleviate long-term poverty are best targeted with PMT scores from the unified registry, potentially with household additions from a community-based or self-targeted approach. The indicators used to construct a PMT score tend to change slowly over time and are best suited to identifying persistent poverty, rather than transitory shocks. Consequently, using the PMT scores solely to target programs is best done when the program objective is to alleviate long-term poverty. This might apply in the case of CCT programs such as PKH. However, households can fall into chronic poverty after the unified registry has been established, through shocks such as natural disasters or catastrophic health events. In this case, households who were not poor at the time the registry was first constructed can be allowed to enter program lists through other means. Households could apply to join the program from outside of the registry list, but an independent means of verification would be required. Community-based verification may be the best

87 The following material has been summarized from Coady, Grosh and Hoddinott (2004).

supplementary approach in these circumstances, as members are likely to know whether the applicant has been subject to a significant and lasting shock. The level of additions can be capped to minimize the risk of abuse. This is discussed in the next section.

Programs designed to protect households from falling into poverty can be targeted broadly at the most vulnerable population. Other programs are intended to prevent non-poor households from falling into poverty. Consumption-based PMT scores constructed before any household shocks are not as useful for targeting these programs. There are at least two possible approaches. The first is to try and identify which households are most vulnerable, using a non-consumption PMT score. For example, households with incomes vulnerable to shock or with few available coping mechanisms could be identified by constructing a vulnerability PMT score, based on source and type of income, a wealth PMT (see Section 6.1), and community-connectedness measures. A second approach is to target such programs broadly, to those households from whom most of the new poor will come. As discussed in Section 1, over 80 percent of the Indonesian poor in any year come from the poorest 40 percent of people in the previous year. Targeting programs supporting the vulnerable to this group, as identified by registry PMT consumption estimate, would effectively cover most households who enter poverty in any particular year. Additional households, up to a set quota, could be allowed to enter these programs from a combination of self-targeting and community verification, as discussed in Section 7. It is important to note here that the single easiest way to improve targeting accuracy of poor households is to increase program coverage above this level. Of course, this broad-based approach would be subject to fiscal sustainability of having such large programs. Fortunately, Indonesia is well-placed to enact programs of such scope (see World Bank 2012d).

Programs should be self-targeted when this would be accurate and cost-effective. A small number of programs can be self-targeted with confidence. The successful targeting of public works programs with a below-market wage has been discussed (Box 6.2). Other examples include making low quality food available at a subsidized price to whomever wants to buy it, in whatever amounts desired. However, while this accurately screens out those households who can afford (and prefer) better quality food, it may not be affordable. In a country such as Indonesia where many households still live near the poverty line, the cost of a self-targeted food program is likely to be prohibitive.

Finally, programs deployed in times of crisis or shock may require targeting beyond the NTS. When a shock affects many households at once, such as an economic crisis, a natural disaster, or price increases, then the objectives of public assistance are different, as are the targeting requirements. Assistance must usually be quickly given, and is likely only to be temporary. In such cases, targeting accuracy may be less important. For example, in a natural disaster, assistance can be targeted at particular areas experiencing shock, but then made universal to all households, or in a self-targeted manner that allows any household who wants to participate. Alternatively, if an economic shock leads to high unemployment, a public works response may be appropriate, which is also best self-targeted. The location for such programs could be determined from a Crisis Monitoring and Response System (see Box 6.3). However, not all temporary assistance programs in times of shocks must be targeted without the NTS. For example, when food prices rise sharply or in a sustained manner, it is the poor who will be most affected, since food comprises a much larger proportion of the poverty basket than the average consumer basket.[88] In this case, PMT scores from the registry may still be appropriate for selecting households to receive temporary assistance (whether cash or in-kind).

Box 6.3: Crisis monitoring and response in Indonesia[89]

As the global economic crisis (GEC) which began in late 2008 deepened into 2009, the Government of Indonesia established a temporary Crisis Monitoring and Response System (CMRS), designed to identify how the effects of the GEC was being transmitted to households, how they were responding, and what the socio-economic outcomes were, in order to guide the appropriate public response. The CMRS used existing high-frequency data combined with a quarterly rapid, lightweight household survey fielded in every district. The results assisted the government in determining what responses were required, where, and when. Fortunately, Indonesia was relatively unscathed by the GEC, with economic growth never becoming negative and quickly rebounding.

Nonetheless, a key lesson from the experience was that Indonesia needed a permanent monitoring and response system that regularly monitored household welfare at the district level and identified shocks, and had available a range of responses that could be deployed quickly when required. Work has begun to develop such a system, and this could be used to geographically target crisis responses.

88 Food makes up 65 percent of poor household consumption in Indonesia.

89 For further discussion of Indonesia's experience in household monitoring and response during the recent crisis, see World Bank (2010a). For discussion on institutionalizing such a system in Indonesia, see World Bank (2010b).

6.3 Socialization and Communications

A socialization and communications strategy needs to be developed and implemented. We have seen how critical proper socialization is to all levels of government, as well as to communities, beneficiaries and the general public (see Part A). Without proper socialization, line ministries will be wary of using the unified registry, local governments and communities may include the identified beneficiaries in programs, local communities may redistribute benefits, and beneficiaries will not know their rights and entitled transfers. A comprehensive socialization plan, combined with an ongoing communications and media strategy is essential, in addition to the socialization required for each program on other operational aspects.

07

Maintaining and Updating a National Targeting System

This section looks at two very important functions for maintaining and updating an NTS. These are handling complaints and grievances, and recertification of beneficiary data. Other issues are briefly addressed. How complaints and grievances are addressed, and how beneficiary data are updated and recertified are key issues in maintaining an NTS. They are explored in more depth in this section. Addressed briefly but equally as important is monitoring and evaluation, as well as the potential relationship between program exit strategies and an NTS.

7.1 Complaints and Grievances

A complaints and grievances redress mechanism that quickly and satisfactorily resolves disputes is critical to support local buy-in of the NTS. An integral capacity of an NTS is to handle complaints, grievances and appeals presented by different stakeholders including prospective beneficiaries, user programs, the general public, and control and oversight agencies. The grievance redress system needs to include a detailed description of the different types of complaints and grievances that can be made, where they can be made, who has to capacity to resolve them, the time it should take to address them, and the mechanisms for appeals. The most common complaints are usually related to poor households being excluded from a program, either because they were not assessed as poor previously, not assessed at all, or have recently become poor, as well as non-poor households being included. The grievance redress system needs to establish clear procedures to address all types of errors.

A process for handling complaints will need to be coordinated with each participating program. Households generally will not know their status in the unified registry before program beneficiary lists are extracted. Consequently, they are only likely to complain once these beneficiary lists are announced, either because they have been excluded or because another household they consider undeserving as been included. As a result, an NTS will need to develop a coordinated process with targeted social assistance programs to ensure these complaints are passed from the local program officials receiving them through to the NTS complaints handling function.

A household can be incorrectly excluded from an NTS's program beneficiary list for one of two reasons. If a household's PMT score is above a program's eligibility threshold, yet its true underlying consumption was low, then the household will be incorrectly excluded from the program. In this case, the exclusion error is due to inherent statistical error in PMT models. Alternatively, if a household was not enumerated as part of the initial NTS data collection, then it will not appear in any program lists, regardless of the PMT score it would have received. The statistical error is an error of selection. The non-enumeration is an error of collection. Each error has different implications for an appeals process.

Complaints due to non-enumeration of a household, or incorrect household information being recorded, can be addressed with by a verification process. One of the most common complaints will be from households who have been excluded from a beneficiary list. The easiest to address will be if a household has not previously been surveyed, or if previous data collection has recorded information incorrectly. In these cases, the households can be (re)surveyed with the standard PMT instrument, and new PMT scores constructed. Those households with PMT scores below the program threshold can then be added as beneficiaries. For example, if the NTS MIS indicates that a household has not previously been evaluated, then Statistics Indonesia (or another agency) can conduct periodic PMT verifications of these households. Alternatively, if the household is already included in the MIS, but their demographic data are wrong (such as a household with a qualifying PMT score for PKH but which has been recorded as not demographically eligible), a simple verification of the correct data is required.

The more problematic complaints are those which could be due to statistical error. Policy makers will need to decide whether an alternative evaluation method is to be used to resolve these. If a household complains about their exclusion from a program, but the MIS indicates they have previously been enumerated and the PMT score indicates they are ineligible, there are two possibilities for resolving the complaint. The first is to verify the PMT data with a follow-up household visit. If the PMT data are incorrect, then a new score can be calculated, and if below the program threshold, the household can be added as a beneficiary. However, if the data are correct or the new score is above the program threshold, then the household will remain excluded from the program. In this case, the PMT score is held to be the final arbiter of program eligibility. This is the standard approach in other countries, such as Brazil, Colombia and Chile. The alternative approach would be to use a secondary verification process which does not rely upon PMT, in an effort to address the statistical error inherent in PMT which can lead to significant exclusion and inclusion errors. Possible secondary verification processes are discussed shortly.

Complaints that a non-poor household has been incorrectly included in a program can be handled similarly to exclusion errors, with additional formalities. If a complaint is received that a household represents an inclusion error, then the household will already have been enumerated. In such a case, the same options exist as for an excluded household already in the unified registry. That is, the included household can be resurveyed, with the revised PMT score being the final arbiter of whether the household should remain as a program beneficiary. Alternatively, the household can undergo a non-PMT secondary verification process. However, in addition to these resolution options, an NTS might also require the complainant (who will not be a member of the included household) to formally and publically record the complaint, in order to reduce malicious or trivial complaints. Grosh *et al.* (2008) note that such complaints may be rare, in the case that the included household has a high public stature or influence, for fear of reprisal. In such cases, they suggest that a local NGO also be able to lodge a complaint.

Secondary Verification Alternatives to PMT

The main alternative for conducting a non-PMT evaluation of household appeals is some form of community-based verification. Communities can be involved in verifying beneficiary lists in two ways. First, some or all of a proposed beneficiary list could be verified by the community before implementation. Second, households who feel they have been unfairly excluded can appeal the outcome (a form of self-targeting), and then have their status verified by a panel of community members or at a broader community meeting. The initial evidence from the second targeting experiment suggests that households applying for assessment (self-targeting) are poorer than households on the earlier PPLS08 list, and much more likely to be very poor (see Box 7.1). Whether from an appeals process initiated through self-targeting, or direct verification of lists, there are a number of options for conducting a community verification process, the choice of which is likely to influence its effectiveness.

Box 7.1: A field experiment compared a proxy means test to households self-targeting themselves

In 2010 and 2011, Statistics Indonesia, the World Bank, and J-PAL conducted a second field experiment to examine both the feasibility and effectiveness of community verification and self-targeting methods when used with Indonesia's conditional cash transfer program PKH (see Box 2.5 for discussion of the community method).

In the 200 villages that used the self-targeting method, trained facilitators held community meetings to announce the PKH program and an application process. In some villages, the application process was held in the sub-village or village office, whereas other village members had to visit the sub-district office. This was intended to test whether the additional effort discouraged non-poor households from applyinh. In half of the self-targeting villages, both the head of household and spouse were asked to attend, whereas in others one of the two was sufficient. Applicants were then interviewed by staff from Statistics Indonesia using the new 2011 PMT questionnaire.

The self-targeting method was successfully implemented in 200 experimental villages across 6 districts. Preliminary results indicate that the method may be useful in targeting very poor households, and particularly useful in updating beneficiary lists in the future. Households added to the beneficiary list using self targeting were about 7 percent poorer than households that would have been on the list simply using PPLS08. In fact, those who would be added as beneficiaries from self-targeting methods were 30 percent more likely to be very poor than those who were on the PPLS08 list.

Communities could verify and modify proposed beneficiary lists extracted by the NTS. One approach to incorporating communities into household verification is to have them verify a PMT-based beneficiary list, with the ability to revise such a list, as is done in Mexico for the Oportunidades CCT program (Grosh *et al*. 2008). A community meeting, either of selected representatives or a broader gathering, could meet to verify the preliminary list issued by the NTS using PMT scores. A key decision would be whether the community could remove households from the initial list which they believe to have been incorrectly included, or only add households they feel incorrectly excluded. The former is more likely to be divisive and create social conflict, and in practice seldom happens in other countries (Grosh *et al.* 2008). In order to retain a central role for the PMT scores, a limit could be placed on the number of households a community can add (and subtract), meaning that the poorest households by PMT score would be retained, with the community adding only a fixed number of households (or possibly substituting further households for some of those on the PMT list).

This form of community-targeting could reduce exclusion error and increase community satisfaction and buy-in. There are several possible advantages to adopting such an approach. Genuinely poor households which would be excluded by PMT can be included on final beneficiary lists, and at least some are likely to be included because of the additional local knowledge of communities. This local knowledge can also account for households who fall into poverty after the initial data collection was made, and thus will better address transient poverty, which PMT is not well suited to identify. Moreover, community satisfaction with the targeting process and outcomes is likely to be higher. Greater satisfaction may well subsequently reduce the degree of informal deviation from NTS targeting lists (as currently experienced, for example, with Raskin). Section 2 has discussed the field work in Indonesia which has already explored some of these approaches in Indonesia. In the case where communities select beneficiaries themselves, but also when they select households to receive a PMT enumeration, satisfaction with targeting outcomes are higher than with PMT selection alone. Follow-up field work was conducted in 2011 to test whether exclusion errors are reduced by exactly the verification process outlined here. Full results of these pilots will become available by early 2012, and should provide important evidence for policy makers on the effectiveness of such an approach. Initial results already indicate this is a promising approach (see Box 2.5).

Nonetheless, careful design and evaluation would be required to ensure consistency of application and avoid elite capture. The key dangers in having a secondary verification are the possibilities of corruption or nepotism in the decision-making process, or an inconsistent application of the process in different places. When communities are able to add (or subtract) households to PMT lists using their own knowledge, but also subjective criteria, then there exists the real possibility of non-poor households being included. This risk is likely to be higher when only community elites, such as the village head, are conducting the verification, rather than by a broader community meeting. In such circumstances, friends and relatives may be added, regardless of economic status. Even in broader meetings, the community elite may be able to dominate the process. The field work in Indonesia already discussed does not find evidence of elite capture (see Section 2), but the results of the second field tests which involve much higher benefit levels (PKH membership) will be important in confirming this result, and thus whether a community approach is desirable. However, it may be possible in practice to limit these dangers through careful process design, training and implementation. Restricting the number of households that a community can add or substitute would limit the possible degree of capture, in addition to minimizing the risk of community fatigue in the ranking process. Ultimately, the likely effectiveness of this process will depend in large part upon the skill and capacity of the facilitators of such meetings.

An alternative use of communities in complaints and grievances is to create a local appeals committee. Instead of having communities or their representatives verify beneficiary lists in a systematic way, a community committee could instead be used just to resolve individual appeals. In Armenia, local social protection councils have been established, with five representatives of local government social sector offices and five representatives of non-governmental organizations. These councils can hear appeals from households which have been excluded from programs, and have the right to grant entry to up to 5 percent of the program beneficiary quota (Grosh *et al.* 2008). A similar approach could be adopted in Indonesia, which would reduce the capacity requirements for facilitation and training. However, an appeals committee process without facilitation or broader community scrutiny could increase the likelihood of elite capture and make resolution of appeals inconsistent from community to community.

Instead of community representatives, trained social workers could also be used to resolve appeals, but this is unlikely to be feasible in Indonesia. In some countries, a social worker is used to assess a household's eligibility for assistance programs, whether as the main form of evaluation or to resolve complaints. In this case, the trained social worker can interview and assess the appealing household and make a binding determination as to whether they are indeed eligible, regardless of PMT score. Such a process can be quite effective in reducing statistical exclusion and inclusion error, but requires a high degree of capacity on the part of the social worker. However, there is currently no such cadre of workers in Indonesia who could perform this function, certainly not on a national basis and with consistency of performance.

Reducing the Likelihood of Appeals

Another way of addressing targeting complaints is to reduce their likelihood. Section 4 has discussed the importance of collecting data from the right households. If all households are surveyed with a PMT questionnaire, then the main source of targeting error is due to the statistical error of the model. However, if poor households are not surveyed at all, then they are certain to be excluded from the initial registry, regardless of model accuracy. Since it is not practical to survey all households in Indonesia, then reducing the number of poor households excluded from the PMT enumeration is an important part of reducing the likelihood of appeals later. One way of including possibly poor households is to make sure that existing program beneficiaries are included in the survey listing. Another is to use community referrals.

Communities could be involved in data collection by identifying potentially poor households to then undergo PMT verification. Instead of (or in addition to) using communities to verify a PMT-based list of beneficiaries, they can also identify poor households who have not been included on the PMT survey listing. If communities can identify potentially poor households, it can reduce the number of poor households which are not considered for programs. As these households are subsequently evaluated by PMT, the risk of elite capture is greatly reduced. Such an approach has been used in part in Indonesia during the PPLS11 initial data collection. In this process, a household on the initial PMT pre-listing (see Section 4) was selected to provide peer referrals. This household invited two other households they considered of similar economic status to an informal meeting held by a Statistics Indonesia official, where they nominated other households for enumeration which they considered poor but were not on the pre-listing. However, it is important to note that the possible benefits of community involvement in targeting, such as increased community satisfaction with the targeting process and reduced targeting errors from the PMT models (see Section 2) are much less likely from this inclusion of community, as households remain subjected to a PMT verification, and the connection between the community process and final beneficiary lists is more remote.

Updating Household Data

Updating household information as it changes is another important design element of the NTS. An NTS appeals system must will need to deal not only with households who believe a mistake has been made in initial evaluation, but also with households who circumstances change over time. For example, a household with a very low PMT score but no pregnant women or children would not be included on initial PKH lists. In the future, however, the household demographics may change to make it eligible. In such a case, the household might appeal to the PKH program for enrolment. Alternatively, a household with a PMT score above the PKH threshold may subsequently experience the death of the head of household, and also appeal to the program for inclusion. The NTS complaints system will require protocols to deal with such examples. A data updating protocol should specify acceptable reasons for updates (the information allowed to be updated, such as new additions to a family roster or a change of address), how these updates are made (how, to whom and where), and when such updates are allowed. Updating is complex, as it can be manipulated by prospective beneficiaries. Households with too high a PMT score may request an update and provide different and false information. A major dilemma is the frequency with which new information should be accepted from prospective beneficiaries. In Colombia, updates can be submitted nearly as frequently as a beneficiary wants, and there is evidence of both abuse and high costs to the agencies charged with handling the updates.[90] Another option is to close the registry for a certain period of time, say 6 months or a year, although this becomes a problem for people who recently entered poverty during this period and would qualify for government assistance. An associated challenge is the development of an MIS able to handle updates in the master registry and to share the updated information with partner agencies on a regular basis.

Complaints and Grievances in Indonesia

In Indonesia, at least initially, the complaints and grievances process could be tailored to individual programs. It may be desirable to approach targeting appeals on a program by program basis. For example, different social assistance programs have different capacities to implement an appeals process, but may also benefit from different methods. A differentiated approach is also consistent with complaints being received at a local program level. This sub-section discusses how PKH and Jamkesmas could implement quite different appeals resolution processes, reflecting the different nature of each program.

The small size of PKH means expected statistical errors from PMT are relatively high. As a consequence, inclusion of a community-based mechanism in the complaints and grievances process could be adopted. PKH currently has around 1 million beneficiary households, with plans to expand nationally to 3 million households by 2014, or 5 percent of all households in Indonesia. Given additional demographic eligibility requirements, this means trying to target around the poorest 7 percent of Indonesian households. For programs with a low coverage such as this, the expected PMT statistical errors for this very poor group can easily exceed 50 or 60 percent. Ultimately, significantly increasing coverage size is the only reliable way in which to substantially reduce these errors. Moreover, those households included in the program by the PMT models who are not in the poorest 7 percent are likely to be in the poorest 10 or 20 percent, and would still benefit greatly from assistance. Nonetheless, an appeals system could be established with the objective of reducing exclusion of the very poorest. Such a process would likely require the involvement of communities in a manner described earlier; either verification of proposed beneficiary lists, or as a committee to resolve individual appeals. Under the first approach, part of the beneficiary quota could be filled from the NTS database according to household PMT scores. In addition, a community meeting could be used to add further households, subject to a fixed limit (or a substitution requirement for household on the initial list). This meeting could be an open meeting of all community members, or a closed meeting of selected community representatives (such as local officials, teachers, health workers, and

90 See Castaneda and Fernandez (2003) and National Planning Department of Colombia (DNP) on the most common updates presented in Sisben II and III systems (www.dnp.gov.co/Sisben). According to the DNP, two of the most common updates are to include more family members and change the place of residence to rural classification where the point scores are more generous.

religious leaders). The recent field work discussed in Section 2 is designed to determine the accuracy of such an approach, and initial indications are positive.

However, the application of community meetings to verify beneficiary lists in Indonesia is limited by the lack of trained community facilitators. Effective implementation of such community meetings, whether of selected elites or the entire community, would need to be carefully facilitated if the risks discussed previously are to be minimized. It is unclear in Indonesia which public agency would be able to support such an initiative, as the obvious alternatives lack the capacity or national coverage required. For example, Statistics Indonesia's strengths lie in enumeration, not community facilitation. Moreover, their involvement in such facilitation would increase the dangers for reputational risk (see Section 5). Implementing agencies, such as Kemensos (BLT), Kemdiknas (Scholarships), Kemenkes (Jamkesmas) and Bulog (Raskin) do not currently have the experience or capacity at a national level. In the case of the PKH program, the program's own facilitators could be used. However, such a role could create a conflict with the facilitator's primary role (to socialize the program, provide support to beneficiaries in accessing the program and meeting conditionalities, and developing strong knowledge of local conditions and households, which requires trust from the local community). Program facilitators may become less effective in their primary roles if they are involved in decisions on inclusion and exclusion which reduces trust from beneficiaries and the community.[91] If the time and financial resources required for community verification of full program lists, or the lack of institutional capacity to implement such a process, make such an approach infeasible, then the use of community appeals committees to resolve individual appeals on a case-by-case basis might be preferred, subject to a restriction on the number of appeals which can be approved.

With the lower expected PMT statistical errors for a program of Jamkesmas' size, the complaints and grievances process might focus on issues of data collection. Targeting errors are lower for programs with higher total coverage of the population (see Technical Annex 1 of this report and World Bank (2012b, 2012c)). For Jamkesmas, a program covering nearly one-third of all Indonesians, less than 15 percent of the official poor are predicted to be mistargeted under the PPLS11 PMT (see Section 4). If Jamkesmas coverage increased to 40 percent of the population, this error rate might fall to only 10 percent. Given these relatively low model errors, it might be decided to focus Jamkesmas' appeals process on whether a household had been previously assessed by the NTS; if a household has not been surveyed for the PMT, then it cannot become a beneficiary under any model. Such a process would require a reliable MIS available at the district level. When a household lodges an appeal through the local government or Jamkesmas official, a search would be conducted of the NTS to see whether they had previously been enumerated. If they had not, then the data collection agency of the NTS (currently Statistics Indonesia) would conduct a household visit and collect data on the required PMT variables. If the subsequent PMT score was below the Jamkesmas threshold, then the household members could become Jamkesmas members. However, in the case that a household had been previously enumerated, but their resultant PMT score had been above the program threshold, then the appeal would be rejected. That is, for a program of Jamkesmas' size and expected statistical error, focusing on evaluating households who had missed previous data collection efforts may be the most appropriate for resolving complaints and grievances.

Coordination between central and local governments might mean local health insurance initiatives can better act as a safety net for poor households excluded by model error. Many local governments currently fund provision of additional health cover for households excluded from Jamkesmas. These local initiatives are collectively called Jamkesda. Targeting of Jamkesda varies from local government to government (see Section 1). However, stronger coordination between the NTS, Kemenkes and local governments might improve the role of Jamkesda to act as a supplementary benefit for poor households excluded from Jamkesmas.

91 Alternatively, PNPM facilitators could be used to assist in household-targeted complaints resolution. The risk of conflict with their primary role may be reduced, as these facilitators are not related to any particular household or individual assistance program, but rather work with communities as a whole in order to develop community infrastructure and build social empowerment. However, much more work would be required to understand the advantages and disadvantages of incorporating these facilitators in a household-focused appeals system.

7.2 Recertifying the Registry

It must also be determined how frequently and in what manner to recertify beneficiaries. More frequent recertification reduces exclusion and inclusion errors, but is more costly. A common aspect of national targeting systems is the need for recertification over time, generally every two to four years. Recertification involves revisiting all households in the unified registry, as well as other households who may merit evaluation. How frequently this is performed is a key design question for the NTS. More frequent recertification means households who fall into poverty in between recertifications spend less time excluded from social assistance programs (and households climbing out of poverty are removed from programs more quickly). However, recertification is costly and requires considerable human resources to conduct.

A key consideration is how frequently households move into and out of poverty, the nature of the programs being targeted by the NTS, and the effectiveness of the complaints and grievance system. One factor when choosing the frequency of recertification is the period of time it takes households to show significant changes (resulting from social programs or economic activity) on the dimensions being assessed by the national targeting system. When the main consideration is to address structural (long-term) poverty and proxy means test methods are used, the recertification period is typically longer (say, four years), recognizing that changing structural conditions of poverty requires time for government programs and economic activity to produce measurable results. Where the main concern is the evolution of current poverty, the recertification period is typically shorter (one to two years). Furthermore, the importance of recertification depends also on the effectiveness of updating and complaints and grievances systems. If households who fall into poverty, were in poverty but misclassified during initial data collection, or not included in the data collection, are able to become program beneficiaries through a frequent and effective appeals system, then recertification can happen less frequently. However, if an appeals system is ineffective or proceeds slowly, recertification more frequently is desirable.

Indonesia currently recertifies its database of the poor and vulnerable every three years. An important question for the future is who should conduct the recertification in the future? Statistics Indonesia has conducted the major targeting data collection efforts every three years since 2005 (Box 4.2). However, as discussed in Section 4, this role is not performed by the national statistics agencies in other countries. A key reason for this is the danger of reputation risk if the agency is involved in selecting beneficiaries for social assistance programs; this may lead to households giving false responses to important surveys and the population census. However, there is currently no other agency with the capacity to implement a very large-scale PMT survey. A question for the NTS institutional arrangements in Indonesia is whether Statistics Indonesia should continue to perform this role. The alternative would be to build capacity over time in another agency. In the Philippines, for example, the Department of Social Affairs conducted the initial PMT data collection for the country's CCT program, which is now used to target other social assistance programs. This required a significant investment in training, but was ultimately successful. Statistics Indonesia expertise and technical assistance from international aid institutions could be used to build similar capacity in Indonesia. Candidate institutions to develop such long-term capacity might include Kemensos and the targeting unit of TNP2K. Pilot implementation could be done in conjunction with Statistics Indonesia during updating activities in 2012 and 2013, prior to the 2014 PPLS recertification, or with a longer time horizon in mind.

7.3 Monitoring and Evaluation

Strong monitoring and evaluation is critical to ensuring implementation as planned, targeting outcomes are accurate, and the system is cost-efficient. Monitoring should include the initial registry, checking it with other program records to detect duplications, and sharing the data with partner agencies. These activities can use regular administrative data, or conduct spots checks or rapid operational evaluations. Evaluations of targeting outcomes require collecting data on random samples to investigate program incidence and coverage for different target populations, with inaccuracies being used to refine future applications of the targeting system. The analysis used in this report with the regularly collected Susenas data can be repeated each year to monitor targeting accuracy and identify program lists or geographical locations requiring improvements.

7.4 Program Exit Strategies

It is good international practice for programs to have exit strategies. Exit strategies are often applied in targeted social programs, in order that households do not stay in a program indefinitely, particularly when they no longer need assistance. Many programs include time limits or automatic exit of certain demographic groups when they no longer meet eligibility criteria, such as in the Temporary Assistance for Needed Families (TANF)[92] in the United States, and welfare programs in other OECD countries, or require frequent (re)application such as in Eastern European countries. However, often social assistance is open-ended, meaning it is unclear how a household ceases being a beneficiary.

Programs can use a fixed period enrolment to implement an exit strategy. Many programs, such as the increasingly widespread Conditional Cash Transfer, (e.g. Mexico, Colombia, Honduras, Nicaragua, Turkey, Philippines, Indonesia) enroll beneficiaries for a longer time period, generally five years or more. These beneficiaries remain in the program as long as they meet the program conditionalities for the established duration of the program.

Another common exit strategy in developing countries is to provide incentives for people to move out of the concerned social welfare program. These strategies include training and loans for micro-enterprise development, scholarships for high achieving students, promoting savings in the financial system to avoid abuses by private lenders, among others.

A National Targeting System can also facilitate program exit strategies through its periodic updating or recertification. For programs without a current exit strategy, such as Jamkesmas, whose cards do not expire, an NTS can provide a natural exit – or at least recertification – strategy. As discussed earlier, targeting systems often recertify households every three or four years. In many cases, such as with the Subsidized Health Insurance for the Poor in Colombia, programs opt for automatic enrolment every year while the targeting system is current. When recertification is conducted, beneficiaries no longer meeting the poverty score requirements are delisted.

92 See Lindert (2003).

08

Recommendations and Future Directions

An NTS is a dynamic system that needs to evolve over time. The final section of this report focuses on the evolution of social assistance in Indonesia and its implications for future development and use of an NTS in Indonesia. This section also provides a summary of recommendations contained in the report.

8.1 Summary of Recommendations

Targeting is a critical determinant of the effectiveness of Indonesia's current social assistance. Substantial improvements can be achieved through a national targeting system, but they must be designed and implemented carefully. Targeting of social assistance programs in Indonesia can be improved substantially, as current targeting is fragmented, and many poor households are excluded from programs at the same time that many non-poor receive program benefits. Socialization of program objectives, beneficiaries and benefits is weak and often adversely affects program and targeting outcomes. Program buy-in can be affected by community and media dissatisfaction with program implementation and perceived mistargeting. There is no real way for complaints and grievances to be made or addressed. A national targeting system with a unified registry of potential beneficiaries at its heart, used by all social assistance programs, could help resolve many of these issues. Table 8.1 summarizes the recommendations of this report.

The targeting of social assistance and protection in Indonesia can be improved significantly with the development of a National Targeting System. Such a system can provide improved targeting accuracy in a cost-effective manner, while generating increased buy-in for social assistance from politicians, ministries, local government, communities and beneficiaries.

Table 8.1: Recommendations at a Glance: Towards a National Targeting System

Component	Recommendations
Design	
Targeting Objectives	The targeting objectives of each social assistance program need to be carefully and clearly defined.
Legal and Institutional Framework	An institutional framework needs to be developed that clearly allocated responsibilities and authorities within an NTS, including who collects which data, who analyzes it and how, and who can use it. These arrangements should have a clear mandate in enacted legal regulations.
Initial Data Collection	Initial data collection for the unified registry of potential beneficiaries should be based on the PPLS11 carried out by Statistics Indonesia in July 2011. Data collection needs to focus on collecting the right information from the right households. Collecting the right information means coordinating with line ministries to identify the data required to target each social assistance program. Visiting the right households means including as many potentially poor and vulnerable households in the initial survey as possible. In order to reduce exclusion errors, incorporation of existing program lists should be considered.

Implementation	
Building a Unified Database	An initial database of potential beneficiaries is required. Developing this database should include data integrity processes, such as checking for duplications and fraud control. Careful considerations need to be given to overall MIS design for hardware and software, based on planned use and data sharing arrangements.
Extracting Program Beneficiary Lists	A unified registry should not be seen as a single list of beneficiaries for all programs, but as a source of high quality data on potential beneficiaries. Separate processes should be used to identify beneficiaries for each program. This should coordinated with line ministries, and factor in program complementarities, such as ensuring all PKH beneficiaries also receive Jamkesmas. Data sharing arrangements should govern rights and responsibilities of the unified data for each participating agency.
Socialization and Communication	A comprehensive socialization strategy should be developed. This should cover all issues, such as individual program objectives and intended beneficiaries, and rights and benefits of beneficiaries, as well as how beneficiaries were selected and a clear process for appeals. In addition, the strategy should reflect the different needs for all stakeholders, including central and line ministries, parliament, local government, communities and civil society, and beneficiaries themselves. This strategy will need to be developed in coordination with line ministries and the Ministry for Communication and Information (Kemenkominfo).

Component	Recommendations
Maintenance and Updating	
Complaints and Grievances Protocols	A well-designed and communicated complaints and grievances redress process is critical. Such a process should specify what appeals can be made, how they should be resolved, and by whom. Strong consideration should be given to the possible inclusion of community input in this process, but such a role needs to be carefully designed and facilitated.
Updating and Recertification Protocols	Clear guidelines are required as to what information can be updated in the NTS, how frequently, and how it will be verified. Who will carry out household visits in the future needs to be resolved now. Statistics Indonesia continues to be exposed to reputation risk through its current involvement in beneficiary selection, which compromises its other products such as the decennial Population Census and quarterly Susenas and Sakernas surveys. However, if another agency is to adopt this role in the future, then significant investments in capacity building are required.
Monitoring and Evaluation	Regular monitoring and evaluation is required to assess targeting performance, identify areas and methods for improvement, and identify implementation issues. These efforts should be coordinated with general program effectiveness M&E activities of line ministries.
Program Exit Strategies	Coordination of program exit strategies with the NTS should be done with line ministries. Where beneficiaries automatically graduate from programs, such as PKH or scholarship, the NTS needs to track this. Where program exit strategies are unclear, as with Jamkesmas, there exists the opportunity to align this process with the recertification of the NTS's unified registry.

8.2 Evolution of Social Assistance and Protection Strategies and the National Targeting System

Targeting in Indonesia occurs in a difficult environment, but Indonesia has made good progress towards improved targeting outcomes. With 240 million people across some 18,000 islands, a high degree of budgetary and governance decentralization, high rates of entry and exit in poverty, and relatively low inequality of consumption in Indonesia, targeting in Indonesia is difficult and complex. Historical targeting outcomes in Indonesia have generally been pro-poor, but with many poor still excluded from social assistance programs, and significant improvement possible. These improvements are both methodological and operational. Good progress has already been made towards implementing such improvements. The recent PPLS11 data collection of 25 million potentially poor and vulnerable households represents an important advance in the quality of targeting data collection in Indonesia.

However, improvements need to be continuous and there is much still to do. Updating and recertifying the unified registry will be critical to ensure the data do not become obsolete. While PPLS11 is an excellent start to improving targeting in Indonesia, there is still much to do. A unified registry of potential beneficiaries needs to be developed from PPLS11, which involves developing scoring models for different programs and extracting beneficiary lists from these scores. Data sharing arrangements need to be agreed with participating programs. MIS, complaints and grievances, and monitoring and evaluation functions need to be developed. The resulting NTS needs to be socialized to all stakeholders, including central and line ministries, local government and communities, and beneficiaries themselves. Perhaps the most important processes to develop will be determining how to update and recertify the unified registry over time to prevent the data becoming obsolete.

Such continuous improvements require an investment of both time and resources. They also require a commitment from future administrations to keep progressing towards better targeting. While the investment of resources required to develop an NTS is a very small proportion of the total public spending on the social assistance programs supported by it, this investment of both time and money needs to be made. Moreover, the investment cannot stop once the initial registry is established, but should continue on an annual albeit lower basis to support the effective functioning of the NTS over time. This commitment to investing in improving targeting outcomes in Indonesia needs to be maintained by future administrations as well as the current one. A critical step towards this will be determining the long-term institutional and legal framework required to support the NTS over time. Finally, developing an effective unique national individual and household identifier is vital in order to facilitate stronger program coordination and reduce fraud and abuse.

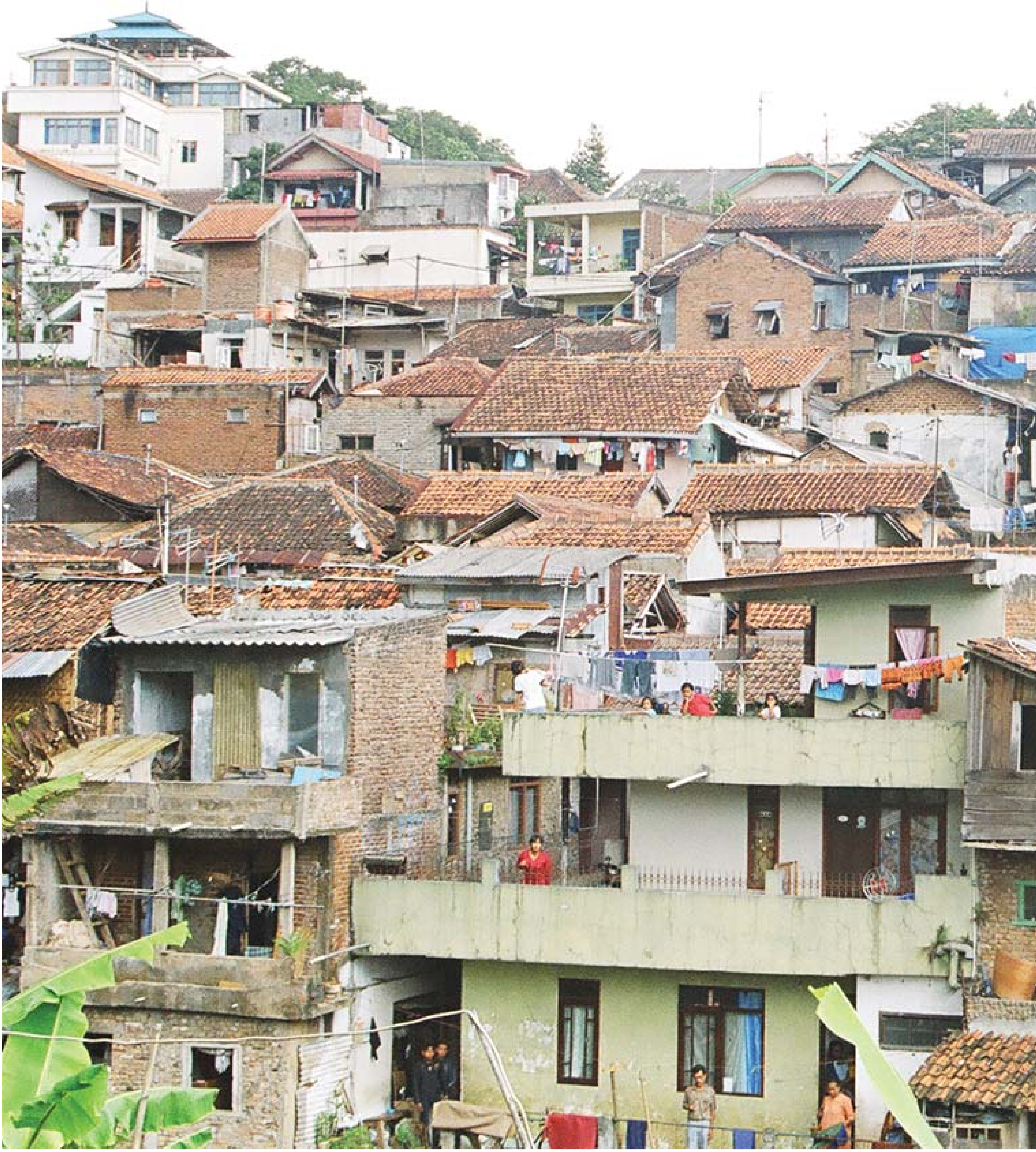
Once established, an NTS can be used more broadly than just for social assistance programs. It can also facilitate discussion about the nature of social assistance as a whole. Once an NTS has been developed, it can be used by not only all social assistance and protection programs, but also other government initiatives. For example, it can be used to support agricultural extension services to poor farmers, initiatives to increase financial inclusion amongst the poor and vulnerable, or the targeting of household-specific subsidies for utilities. More importantly, once there is a tool to ensure that programs can use a single, reliable mechanism to target a variety of programs, it facilitates the thinking about the benefit packages as a whole. Who is eligible for multiple programs? Do they add up to a sensible amount in total and provide complementary coverage? Or do are there awkward gaps and overlaps? The present situation in Indonesia is more of the latter, with some key gaps in some areas of the social assistance strategy, ineffective programs in other areas, and a spending mix that could be better balanced between components and higher in aggregate (see *Protecting the Poor and Vulnerable in Indonesia* (World Bank 2012d)).

Finally, as Indonesia continues to develop economically and socially, there is a need to think not just about those living below the poverty line, but the large number of vulnerable living near it. With poverty in Indonesia approaching just 10 percent, it is becoming increasingly important to consider also the additional 30 to 50 percent of Indonesian households who live above poverty line but remain highly vulnerable to falling back below in the case of a shock. Over half of the poor in any particular year will have entered poverty despite living above the line the year before, and over 80 percent of the poor this year will come from the poorest 40 percent in the previous year.

The shape of social protection in Indonesia is evolving in a manner consistent with this additional emphasis on vulnerability. Indonesia is slowly moving forward with a social insurance framework which envisages universal coverage of the country with respect to health insurance, worker accident, death and retirement protection by 2015. Some households and individuals will make contributions towards this insurance package, while others will have their contributions made by the government.

The evolution of an NTS will also depend upon how this evolution of social protection proceeds. An NTS is a living system which evolves over time, as we have seen with the need for appeals, updating, and recertification. However, a more fundamental evolution may be required in line with the transformation of the country's social protection strategy. If the SJSN framework mentioned previously is ultimately implemented, a greater range of programs may involve targeting of households upon whose behalf the government will make contributions. This targeting may well involve additional or different criteria to simply targeting poverty, such as informality of employment.

While much further work is required to design, implement and maintain an effective NTS, many of the elements for such a system are already in place. Moreover, Indonesia has the administrative and fiscal capacity to succeed in this endeavor. Access to social assistance through better targeting means that climbing out of poverty, and being protected from falling back in, can become a reality for the millions of Indonesians who still struggle in their daily lives.



Supplementary Material

9. Technical Annex 1: Targeting Metrics

This annex briefly defines, discusses and compares the different targeting metrics used in this paper. See the 'Targeting Metrics' (World Bank 2012c) for a comprehensive discussion.

9.1 Leakage and Undercoverage

Leakage (also called inclusion error) gives the proportion of beneficiaries who are not from the target population. Undercoverage (also called exclusion error) gives the proportion of the target population who are not beneficiaries. If the total population is N, N_p is the population of the poor, B the total beneficiaries, and B_p the total poor who are beneficiaries, then leakage and undercoverage are given by:

$$Leakage = \frac{(B - B_p)}{B}$$

$$Undercoverage = \frac{(N_p - B_p)}{N_p}$$

In the case that the percent of population receiving transfers is the same as the number of poor, then leakage = undercoverage (as $B = N_p$). It is well known that these are not satisfactory targeting measures (see Coady, Grosh and Hoddinott (2004) and Coady and Skoufias (2004)), since: (i) leakage to a very rich household is considered as an equal error as leakage to a household just barely non-poor; (ii) undercoverage of a very poor household is considered an equal error as a household just barely poor; and (iii) we would think a household barely poor and one barely non-poor should have their welfare considered in similar terms, which undercoverage and leakage do not allow. Moreover they are not comparable for programs of different sizes (see Boxes 2.1 and 2.2).

9.2 Coady-Grosh-Hoddinott

Coady, Grosh and Hoddinott (2004) use the following measure to compare different transfer programs, which represents the portion of the transfer budget received by a population quantile divided by the portion of the population in that quantile. That is:

$$CGH = \left(\frac{\Sigma\, dm^h g^h w^h}{\Sigma\, dm^h w^h}\right) \Bigg/ \left(\frac{\Sigma\, g^h w^h}{\Sigma\, w^h}\right)$$

where g^h is a binary variable taking the value 1 if household *h* is a member of the group of interest and 0 otherwise, dm^h represents the per capita value of the a transfer to household *h*, w^h represents the number of people in the household multiplied by the househ Technical Annex old weight in the survey.

Thus, if the bottom decile of the consumption distribution were to receive 30 percent of the total value of transfers, then the CGH for the first decile, CGH(1), would be 0.3 / 0.1, or 3.0. In the case of random targeting of 20 percent of the population, the first decile would get 10 percent of the transfers, so CGH(1) would be 0.1 / 0.1, or 1.0. In the case that the first decile received 30 percent of transfers and the second decile 20 percent, then combined they receive 50 percent of transfers and represent 20 percent of the population, so CGH(2) would be 0.5 / 0.2, or 2.5. In the case of random targeting of 20 percent of the population, then the first and second decile would receive 10 percent of transfers each and CGH(2) would again be 1. That is, with random targeting, CGH is always 1.0, as seen in Table 9.1. Any form of progressive targeting will mean a CGH greater than 1.

The problem with CGH comes with perfect targeting. By perfect targeting, we mean the case where for a given coverage X percent, the bottom X percent of the distribution all receive the transfer, while no household above the X percent threshold does: that is, leakage and undercoverage are both zero.[93] In this case, for any given coverage level, we would want CGH to be the same, since a desirable targeting metric is scale-invariant. However, as Table 9.1 demonstrates, CGH for a perfect targeting scheme is not the same over different coverage levels. In Panel B, the transfer was perfectly targeted to the first decile, so CGH(1) is 10 (the bottom decile receives 100 percent of transfers and represents only 10 percent of the populations, so CGH(1) = 1.0 / 0.1). However, when we increase the coverage to 20 percent, then with perfect targeting, CGH(1) and CGH(2) are 5.0. The bottom decile receives 50 percent of transfers, so CGH(1) = 0.5 / 0.1 = 5.0. The bottom two deciles receive 100 percent of transfers, so CGH(2) = 1.0 / 0.2 = 5.0. That is, even though the program was perfectly targeted, the CGH measure is different when the coverage level is different.

Table 9.1: CGH with Random and Perfect Targeting and Different Coverage Levels

Panel A: CGH measures with random targeting over different coverage levels					
	CGH measure for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	1.0	1.0	1.0	1.0	1.0
20%	1.0	1.0	1.0	1.0	1.0
30%	1.0	1.0	1.0	1.0	1.0
40%	1.0	1.0	1.0	1.0	1.0
Panel B: CGH measures with perfect targeting over different coverage levels					
	CGH measure for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	10.0	5.0	3.3	2.5	2.0
20%	5.0	5.0	3.3	2.5	2.0
30%	3.3	3.3	3.3	2.5	2.0
40%	2.5	2.5	2.5	2.5	2.0

9.3 Normalized Coady-Grosh-Hoddinott

To address this issue of scale-invariance, we suggest normalizing the CGH measure by its score when targeting is perfect at the intended coverage level. That is, for coverage level X, the normalized CGH (nCGH) is:

$$nCGH\,(x) = \frac{CGH\,(X)}{CGH\,(X)_{perfect}}$$

Thus, for coverage of 20 percent, $\mathrm{CGH}(2)_{\mathrm{perfect}}$ is 5.0. Normalizing $\mathrm{CGH}(2)_{\mathrm{perfect}}$ by itself gives $\mathrm{nCGH}(2)_{\mathrm{perfect}}$ of 1, which means nCGH has the happy feature of being bounded by 0 and 1, with the lower bound meaning no member of the quantile received any transfer, and 1 meaning they all did. As can be seen in Table 9.2, $\mathrm{nCGH}(X)_{\mathrm{perfect}}$ is constant at 1 across increasing levels of coverage. Moreover, when a program is perfectly targeted, nCGH measures at cumulative deciles below the coverage level are also 1, indicating that those deciles were perfectly targeted, a feature CGH does not display. So when coverage is 30 percent, CGH(1), CGH(2) and CGH(3) are 1, indicating perfect targeting for each cumulative decile, with CGH(4) dropping to 0.8, since the fourth decile was not targeted.

93 At this stage we are considering only uniform transfers, so percentage of beneficiaries represented by a given quantile and percentage of benefits received by given quantile are the same.

Table 9.2: nCGH with Random and Perfect Targeting and Different Coverage Levels

Panel A: nCGH measures with random targeting over different coverage levels					
	CGH measure for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	0.1	0.1	0.1	0.1	0.1
20%	0.2	0.2	0.2	0.2	0.2
30%	0.3	0.3	0.3	0.3	0.3
40%	0.4	0.4	0.4	0.4	0.4
Panel B: nCGH measures with perfect targeting over different coverage levels					
	CGH measure for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	1.0	0.5	0.3	0.3	0.2
20%	1.0	1.0	0.7	0.5	0.4
30%	1.0	1.0	1.0	0.8	0.6
40%	1.0	1.0	1.0	1.0	0.8

A consequence of the normalization is that nCGH with random targeting is now no longer scale-invariant. As Panel A of Table 9.2 presents, nCGH is the same as the coverage rate. However, this is not necessarily an undesirable property. If we want a metric that includes a measure of how well identified the target population is, nCGH does just this: if we are randomly allocating transfers, then increasing the coverage level will increase the proportion of any particular decile or cumulative decile that receive a transfer. In other words, increasing coverage rates with random targeting improves our targeting of the target population, which the nCGH reflects, albeit at an increasing cost due to more non-target populations receiving it, which the nCGH does not capture. CGH does captures this in the sense that with random targeting, all CGH are 1, regardless of coverage levels, so overall targeting is deemed not to have improved; the improved coverage of the target population is balanced out by the increased coverage of the non-target population. In summary, nCGH is best used to compare how well targeting performance was relative to perfect targeting (a scale-invariant 1 with nCGH), rather than random targeting (not scale-invariant nCGH).

However, we can easily express nCGH as a gain over a constant value for random targeting instead, rather than holding perfect targeting constant as well. To do this, we simply calculate the gain in actual nCGH of our program targeting over the nCGH of random targeting, at the coverage level of our program. However, because nCGHrandom increases with scale, we need to normalize this measure by the maximum improvement possible, in order to compare across programs of different scales. Thus, our scale-invariant nCGH measure which compares performance to both a constant random targeting rather than and perfect targeting, is nCGH gain, expressed as:

$$nCGH\,(x)\;gain = \frac{CGH\,(X) - CGH\,(X)_{random}}{CGH\,(X)_{perfect} - CGH\,(X)_{random}}$$

$$nCGH\,(x)\;gain = \frac{CGH\,(X) - 1}{CGH\,(X)_{perfect} - 1}$$

As Table 9.3 shows, nCGH gain is scale-invariant for both random and perfect targeting, being constantly 0 for the former and 1 for the latter. Thus the nCGH gain measure indicates how much better than random targeting an outcome was, ranging from 0 percent (the same as random targeting) to 100 percent (perfect targeting), and can be compared directly across coverage levels (although it still does not account for the different degree of targeting difficulty at different coverage levels).

Table 9.3: nCGH gain with random and perfect targeting and different coverage levels

Panel A: nCGH gain measures with random targeting over different coverage levels					
	nCGH gain for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	0.0	0.0	0.0	0.0	0.0
20%	0.0	0.0	0.0	0.0	0.0
30%	0.0	0.0	0.0	0.0	0.0
40%	0.0	0.0	0.0	0.0	0.0
Panel B: nCGH gain measures with perfect targeting over different coverage levels					
	nCGH gain for cumulative bottom X deciles				
Coverage level	1	2	3	4	5
10%	1.0	1.0	1.0	1.0	1.0
20%	1.0	1.0	1.0	1.0	1.0
30%	1.0	1.0	1.0	1.0	1.0
40%	1.0	1.0	1.0	1.0	1.0

In the case of regressive targeting, nCGH gain will be negative. The lower bound (the target group receiving no benefits) is no longer fixed, being given by $-1/(CGH(X)_{perfect} - 1)$.[94] In many cases we will not be evaluating regressive programs. When comparing regressive programs, the nCGH gain could use an alternative normalization to express the loss (in this case) relative to random targeting as a percentage of perfect mistargeting. This would allow regressive programs of different coverage levels to be compared. That is, defining:

$$n \equiv \frac{1}{CGH\,(X)_{perfect} - 1}$$

then

$$nCGH\,(x)\;gain = n\,(\,CGH(X) - 1\,)1_{(CGH(X) \geq 1)} + \frac{CGH\,(X) - 1}{-\,n}\,1_{(CGH(X) < 1)}$$

or, expressed alternatively,

$$nCGH\,(x)\;gain = n\,(\,CGH(X) - 1\,)\;if\;CGH(X)\,1 \geq 1$$

and

$$nCGH\,(X)\;loss = \frac{CGH\,(X) - 1}{-\,n}\;if\;\mathrm{CGH}\,(X) < 1$$

Now nCGH gain is 0 if actual targeting is equivalent to random targeting, between 0 and 1 if progressive, with 1 meaning all benefits received by the target population, and between -1 and 0 if regressive, with -1 meaning no benefits were received by the target population. Note, while regressive programs can now be compared to each other, the progressive and regressive ones cannot, as the normalization is different for progressive and regressive programs. This may be a lesser concern, since progressive targeting is clearly preferred.

104 In general, no single (linear) normalization will allow all three of perfect targeting, random targeting and perfect mistargeting to remain scale-invariant. Since perfect and random targeting are the more natural reference points for assessing targeting outcomes, we choose to fix these points.

9.4 Distributional Characteristic

The distributional characteristic (DC) was initially developed for taxation, but Coady and Skoufias (2004) applied it to transfers. Detailed derivation and discussion can be found in Coady and Skoufias (2004) and Tesliuc and Leite (2010). The DC is given by:

$$DC = \frac{\Sigma_h \beta^h dm^h}{\Sigma_h dm^h} = \sum_h \beta^h \theta^h$$

where β^h represents the welfare weight of household h, and θ^h is the share of total transfers received by household h. Commonly, β^h, following Atkinson (1970), is given by:

$$\beta^h = \left(\frac{y^k}{y^h}\right)^s$$

where y^k is the income or consumption of a household at the threshold (which could be a poverty line or threshold for inclusion in program), y^h is the income or consumption of household h, and ε is the degree of aversion to inequality (increasing from 0, being no aversion – all households valued equally, upwards until it approaches ∞, when the welfare impact on the poorest household dominates the DC, consistent with a Rawlsian maxi-min social welfare perspective).

The key advantages claimed are: (i) value judgments – concern for the poor relative to concern for the rich – are made transparent and flexible; (ii) a broader class of social welfare functions is permitted; (iii) the DC avoids the difficulties of specifying a poverty line; (iv) the DC allows comparison of programs independently of their budgets (size); (v) the DC can be decomposed into targeting efficiency (identification of household as beneficiary) and redistributive efficiency (varying transfer sizes across beneficiaries); and (vi) the DC takes all households into consideration by assigning welfare weights to all.

The decomposition can be performed by adding and subtracting dm^*_{DC} across all beneficiaries, where dm^*_{DC} is the average transfer to beneficiaries (the total amount of transfers divided by the number of beneficiaries with $dm^h > 0$, and with non-beneficiaries receiving $dm^*_{DC} = 0$):

$$DC = \frac{\Sigma_h \beta^h dm^h}{\Sigma_h dm^h} = \frac{\Sigma_h \beta^h dm^*_{DC}}{\Sigma_h dm^h} + \frac{\Sigma_h \beta^h (dm^h - dm^*_{DC})}{\Sigma_h dm^h} = DC^T + DC^R$$

where the derived DC^T represents the targeting efficiency and DC^R the redistributive efficiency. That is, DC^R captures the welfare impact, keeping targeting constant, of deviating from uniform transfers, whereas DC^T captures the welfare impact of having selected the households that became beneficiaries, holding transfer size constant.
As with CGH, DC is not program scale-invariant. Nor is it invariant to the income or consumption distribution at the same program scale. Thus comparing it across programs of different scale for the same consumption distribution, or programs of the same scale across different consumption distributions (such as over time, or between countries), is extremely difficult. However, it can be normalized in a similar manner as nCGH.

9.5 Normalized Distributional Characteristic

The normalization of DC is slightly more complicated than that for CGH, although it follows the same principles. If we were to normalize DC as:

$$nDC = \frac{DC}{DC_{perfect}}$$

then the question arises as to what perfect targeting under DC would mean. In the case of CGH it is straight forward: all of the benefit is received by the bottom X percentile. Perfect mistargeting under CGH means none of the benefit is received by the bottom X percentile. However, since different households within the bottom X percentile (and indeed above it) are weighted differently, this no longer holds.

In the case of uniform transfers, where the program coverage is X, then we suggest perfect targeting means the bottom X percent of households all receive the transfer, and no one else. Perfect mistargeting would mean the top X percent of households all receive the transfer, and no one else. Random targeting means that X percent of random households receive the transfer. [95]

However, a second complication is that coverage can increased by simply reducing the transfer and having more beneficiaries (this could be done at a local level and in contradiction to official guidelines, as occurs in the Raskin program). Thus to calculate $DC_{perfect}$ at a higher level of coverage than that intended by the program does not penalize the actual DC for losses due to dilution of transfer level.

This can be addressed by modifying the DC formula. Recall that the DC is given by:

$$DC = \frac{\Sigma_h \beta^h dm^h}{\Sigma_h dm^h} = \sum_h \beta^h \theta^h$$

In the case of uniform transfers, the use of θ^h is simply the average transfer. We propose substituting θ^h for p^h, where p^h is the proportion of intended transfer received:

$$DC = \sum_h \beta^h p^h$$

For example, if the intended transfer of a program was $100, to cover 25 percent of the population, but local implementers actually gave $50 to 50 percent of the population, then p^h is 0.5. The DC would be calculated as the sum of $\beta^h * p^h$, or the sum of $\beta^h *$ 0.5, for 50 percent of the population. However, for perfect targeting, DC would be calculated as the sum of $\beta^h *$ 1, for the bottom 25 percent of the population; that is, the DC if the program had operated as intended and reached the bottom 25 percent with the full transfer. So, if a program's intended coverage was X, but beneficiaries received 0.Y of intended transfers because the program actually went to Z percent of the population, then DC should be calculated as the DC with p^h of 1 for the bottom X percent, where X is equivalent to 0.Y * Z.

Similarly, random targeting as a benchmark should be that a randomly selected X percent of households receive p^h of 1, and perfect mistargeting as the top X percent of households receive p^h of 1. More clearly, for actual coverage Z, and actual transfer of 0.Y times intended transfer:

$$DC\ (Z) = \sum_h \beta^h p^h = \sum_h \beta^h 0.Y$$

where there are Z households receiving 0.Y,

$$DC\ (Z * 0.\ Y = X\ )_{perfect} = \sum_h \beta^h p^h = \sum_h \beta^h$$

where the bottom X households receive 1,

$$DC\ (Z * 0.\ Y = X\ )_{random} = \sum_h \beta^h p^h = \sum_h \beta^h$$

where a random X households receive 1, and

$$DC\ (Z * 0.\ Y = X\ )_{perfectmistargeting} = \sum_h \beta^h p^h = \sum_h \beta^h$$

where the top X households receive 1.

We can now define normalized DC (nDC) as:

$$nDC = \frac{DC\ (Z) - DC\ (X)_{perfectmistargeting}}{DC\ (X)_{perfect} - DC\ (X)_{perfectmitargeting}}$$

95 In the case of non-uniform transfers, it is less clear. In one sense, having the poorest household receive the entire transfer could be perfect, but the ex-post distribution would not be as improved as if we gave varying transfers to multiple poor households in a manner to make the bottom Y percent of households all have the same consumption.

Since perfect mistargeting is not equal to 0 under DC, given that any household receiving a benefit is treated positively, then we must subtract this lowest possible value first in order to normalize nDC between 0 and 1.
Similarly, nDC gain over random targeting can be expressed as:

$$nDC\ gain = \frac{nDC\ (Z) - nDC\ (X)_{random}}{nDC\ (X)_{perfect} - nDC\ (X)_{random}}$$

Again, the gain of a progressive targeting system will lie between 0 and 1, with 0 representing random targeting and 1 perfect targeting, and the gain being the gain over random targeting. In the case of a negative gain, we have a regressive targeting system; the *loss* can be normalized in such a case to lie between -1 and 0, with -1 meaning perfect mistargeting, and 0 being random targeting. This is done by substituting $nCGH(X)_{perfectmistargeting}$ for $nCGH(X)_{perfect}$ in denominator.

10. Technical Annex 2: Optimal PMT in Indonesia: Additional Results

This annex supplements the discussion of PPLS11 and PMT models in the main report by presenting additional results on PMT in Indonesia. We examine three key issues in designing and implementing a PMT: (i) the effect of adding new variables to the PMT; (ii) how they should be scored, specifically, what geographical level the models should be developed at, which part of the scoring regression they should be calculated over, and what is the result of using a malnutrition as a dependent variable; and (iii) how these scores should be used, specifically, whether just as a ranking or with the level taken into account as well. A more comprehensive look at PMT and how it should be designed in Indonesia can be found in World Bank (2012b), including an evaluation of how previous PMTs in Indonesia have performed, from both a design and an implementation perspective, and the adjustments required to estimate poverty directly from PMT scores.

10.1 Adding New PMT Variables in Indonesia

The most recent PMT model used in Indonesia is called PPLS08, and combines household and community indicators. Statistics Indonesia updated its 2005 list of the poor in 2008. The new list was called Data Collection for Social Protection Programs (*Pendataan Program Lingdungan Sosial 2008*, or PPLS08). The PMT indicators and weights were considerably more sophisticated than those used in 2005, with a range of more than 40 household and village characteristics employed with district-level weights to estimate household consumption levels. [96]

In 2010, five asset variables were added to the Susenas household survey. Susenas, the national socio-economic household survey conducted twice a year, is the main dataset used to construct weights for government PMT scores. The PPLS08 scoring weights were largely determined using earlier Susenas. In 2010, questions on five assets were added to the survey, specifically household ownership of a bicycle, refrigerator, cooking gas tank greater than 3kg,[97] motorbike, and car or motorboat.

A new PMT which includes these new variables results in improved targeting outcomes. We construct a new PMT which uses the PPLS08 variables and adds the new asset variables.[98] Targeting outcomes are presented in Figure 10.1 below. As shown, using the PPLS08, PMT, when conducted on the entire population to select beneficiaries for a program targeting the poorest 30 percent of households, would be 53 percent better than random targeting (out of 100).[99] Selecting beneficiaries based on a new PMT score which adds the asset variables would increase the targeting gain to 57 percent. For a more targeted very poor program (poorest 10 percent), the gain increases from 43 to 48 percent. [100]

96 See Technical Annex 3 and 4 for details of the 2005 and 2008 variables and scoring.

97 3kg gas canisters are distributed at a subsidized price in Indonesia, while those using 12kg tanks do not benefit from the subsidy.

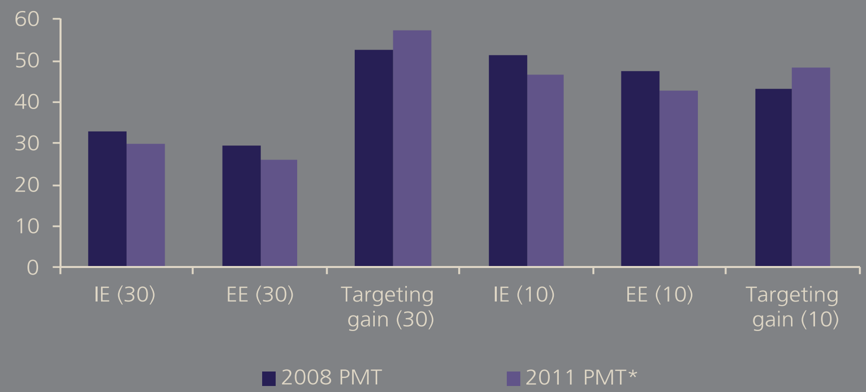
98 Only four are actually added, as one had previously been incorporated, but for our simulation purposes, all five are new.

99 See the main report and Technical Annex 1 for discussion of how to measure targeting outcomes. A few of the variables used in the actual PPLS08 PMT are not available in Susenas and Podes, and so are not included here.

100 The R2 improves by 5 points.

A new PMT which includes these new variables results in slightly improved targeting outcomes.

Figure 10.1: Targeting Outcomes for Two Different PMT Variables Sets in Indonesia



Source: Susenas 2010, Podes 2008 and World Bank calculations.
Notes: * A few of the variables used in the actual PPLS08 PMT are not available in Susenas and Podes, and so are not included here. The variable set for the PMT labelled PPLS08+ is the same as that labelled PPLS08, with the addition of the five asset variables.

10.2 The Effect of Different Levels of Geographical Disaggregation on Scoring Models

The level of geographical disaggregation will depend on the data. There is a limit to how disaggregated PMT models can be in practice, and that is determined by the household survey used for the scoring regressions. The size of a household survey and its sampling design determines how representative it is of the underlying population. For example, in Indonesia, the July Susenas covers around 270,000 households and is representative for all of Indonesia's 471 districts, while the March Susenas covers only 66,000 households and is representative only at the provincial urban-rural level.

More disaggregated models allow variable scores to vary across locations, reflecting local differences. When a model is specific to a particular location, then scoring weights reflect only the influence of the household and community characteristics in that area upon consumption and poverty. Running different models for different areas allows variable scores to vary across the areas, reflecting local differences in geography, the economy, poverty, and social norms. For example, a boat may not be useful in an inland area, but very useful on the coast. Having a goat in a rural area may mean that a household is not poor, but not having one in an urban area does not necessarily indicate that a household is poor. A model which covers all of these areas will result in a single score for each variable, which could result in a counter-intuitive score in certain areas.[101]

However, there are disadvantages to having multiple models based on smaller sample sizes. Estimating PMT models can take time and computing resources. When many models are required, especially if more complicated approaches are being used, then the resource requirement can be extensive. In the case of Indonesia, 471 district-level models would need to be estimated if district-specific scoring was required. Whether this would improve targeting outcomes needs to be determined. Moreover, in practice, a government agency may not have the capacity (knowledge, time, computing resources) to implement such a detailed approach. A more serious problem, however, is sample size. A sample may be representative at the local level, such as at the district level. However, this is for the district population. It is not necessarily representative of the target population within that district, such as the poor and near-poor. Thus conducting a scoring regression on only part of the distribution, or even the full sample, to obtain scores used to estimate the consumption of the poor may result in significant model error when applied outside of the sample to the PMT survey population. This may mean that even when evaluations show a more disaggregated model to have better in-sample targeting outcomes, we may prefer to use a higher level model for those areas with small sample sizes.

101 Including location dummies does not solve the problem, as they will only affect the intercept. Coefficient scores are still constrained to be the same for all locations.

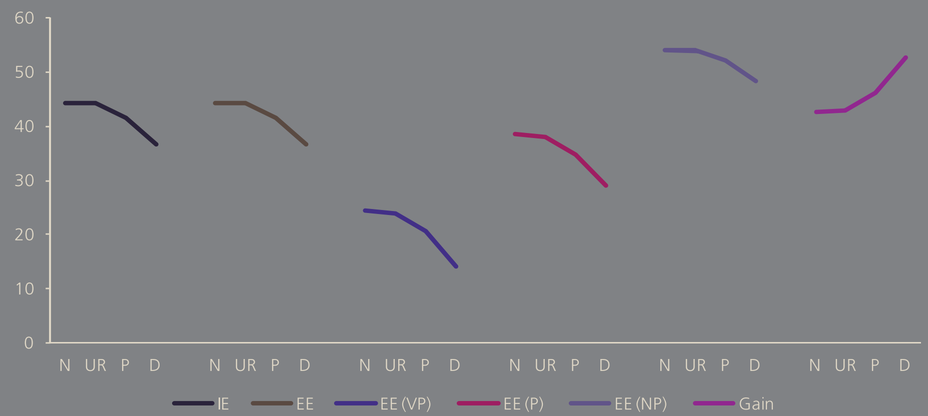
Region-specific Models in Indonesia

Models can be constructed for Indonesia ranging from a single national model down to 471 district-specific models. Using the July Susenas, which is representative down to the district level, we constructed a series of models based on the PPLS08 PMT. Using the PMT scores from each, we assigned households to a simulated program targeted at households below the near-poor line (around 22 percent of households).

Comparing targeting outcomes at the different levels indicates significant gains as we move to greater levels of disaggregation, with the greatest gain being from provincial to district. Figure 10.2 compares targeting outcomes between the different model levels. When a single national model is used, inclusion and exclusion errors are 44.4 percent. This falls nearly 8 percentage points to 36.7 percent when a district level model is used. The greatest improvement is moving from provincial to the district level, which results in a 5 percentage point improvement in errors. The effect is even larger when we consider just poor or very poor households. For the former there is a 9.7 percentage point improvement; for the latter the errors nearly halve from 25 percent to 14 percent. When considering the gain over random targeting, outcomes increase from 43 percent better than random to 53 percent when we move from a national model to a district one. Over 6 percentage points of this 10 percentage point improvement is due to moving from province to district level models. The significant advantage of separate district models reflects the diverse nature of Indonesia, with 18,000 islands, and over 700 languages, and a wide range of socio-economic and cultural conditions. In more homogenous countries the gains in benefits of disaggregating may not outweigh the costs.

Comparing targeting outcomes at the different levels indicates significant gains as we move to greater levels of disaggregation, with the greatest gain being from provincial to district.

Figure 10.2: Targeting Outcomes Using Different Geographical Levels of PMT Models



Source: Susenas 2009 and World Bank calculations
Notes: 1. Level of Model: N – National; UR – Urban-Rural; P – Provincial; D – District. All regressions were over 100 percent of households at the geographic level of the model.
2. Targeting outcomes: IE – Inclusion error; EE – Exclusion error of very poor, poor and near poor; EE (VP) – Exclusion error of very poor only; EE (P) – Exclusion error of poor only; EE (NP) – Exclusion error of near-poor only; Gain – percent improvement over random targeting, out of a maximum of 100 percent (perfect targeting).
3. Poverty levels: 'Very poor' are those households beneath approximately 0.8x the poverty line; 'poor' are those households below the poverty line (but not very poor when calculating the EE here); 'near-poor'are those households below 1.2x the poverty line (but not poor when calculating the EE here). The national poverty line was around Rp 200,000 per month in 2009.

10.3 The Effect of Using Different Parts of the Consumption Distribution for Scoring Models

Targeting is not attempting to accurately estimate all households' consumption levels; it is possible that PMT would be more accurate if scoring weights were based on a poorer part of the distribution. Standard regressions minimize distance from the multidimensional line of best fit. That is, they attempt to predict the dependent variable in a manner that is closest to the true value *on average*. When we are trying to predict a characteristic such as per capita consumption for all households, then it is clear that we should use the entire survey consumption distribution to derive our predictive scoring weights. However, in the case of targeting, we are attempting to identify the poor. It is true that we are also trying to distinguish the poor and near-poor from those who are middle class, but we are not trying to distinguish the middle class from the rich. As such, the question arises are to whether we should be running regressions across the entire distribution, or just a poorer subset of it.

Region-specific Models in Indonesia

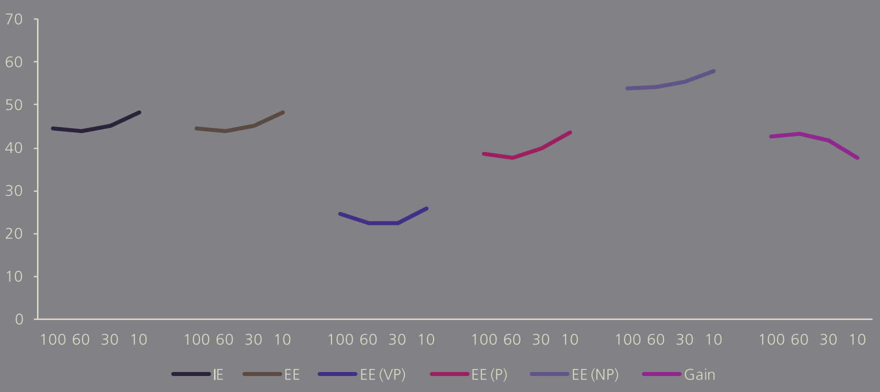
Models can be constructed for Indonesia over increasingly poorer parts of the distribution. Using the July Susenas we constructed a series of models based on the PPLS08 PMT. We ran the scoring regression over four different households samples: (i) the entire consumption distribution; (ii) the poorest 60 percent of households; (iii) the poorest 30 percent of households; and (iv) the poorest 10 percent of households. We did this with a national model and for district-specific models. Using the PMT scores from each, we assigned households to a simulated program targeted at households below the near-poor line.

Comparing targeting outcomes from a single national PMT model which uses scoring weights from different parts of the consumption distribution, results slightly favor using more of the distribution. We can compare targeting outcomes between national models using different parts of the distribution in their scoring regressions, which is presented in Figure 10.3. Inclusion and exclusion errors are 44.4 percent when the entire consumption distribution is used. Errors are within 1.5 percentage points higher or lower if we use the poorest 60 or 30 percent of the distribution, but 4 percentage points lower if we use only the poorest 10 percent of houses in the scoring regression. The same pattern holds when we consider exclusion error for near-poor or poor households. However, error is 2 percentage points lower for very poor households when only the poorest 30 or 60 percent of households are used for the scoring regression. When considering the gain over random targeting, outcomes are similar for 30, 60 and 100 percent of the distribution, but 5 percentage points lower for 10. This suggests when using a single national model that outcomes are not significantly affected if the scoring regression is conducted over the poorest 30 up to 100 percent of the distribution, except for the very poor, who benefit from a model using 30 or 60 percent. On the other hand, no one benefits from a model which uses only the poorest for scoring weights.

The same results do not hold when models are run at the district level. Using only poorer households in the scoring regression leads to considerably worse targeting outcomes. As with the national model results, there is not much difference between models using the full distribution and the poorest 60 percent (Figure 10.4). The very poor and poor are slightly less mistargeted while the near-poor are slightly more mistargeted if using 60 percent rather than 100. Overall targeting gain over random is nearly the same. However, targeting outcomes get much worse for all categories of poor when the poorest 30 percent of households are used for the scoring regression, except for the very poorest, who remain similarly off as when more of the distribution is used. When the poorest 10 percent are used, targeting errors are nearly twice as high on average and targeting gain falls by a factor of nearly four.

Comparing targeting outcomes from a single national PMT model which uses scoring weights from different parts of the consumption distribution, results slightly favor using more of the distribution…

Figure 10.3: Targeting Outcomes Using Different Consumption Distributions for National PMT Model



Source: Susenas 2009 and World Bank calculations

Notes: 1. Level of Model: 100, 60, 30 and 10 are the poorest percent of households which were included in the PMT consumption scoring regression sample. All regressions were run for a single national model.

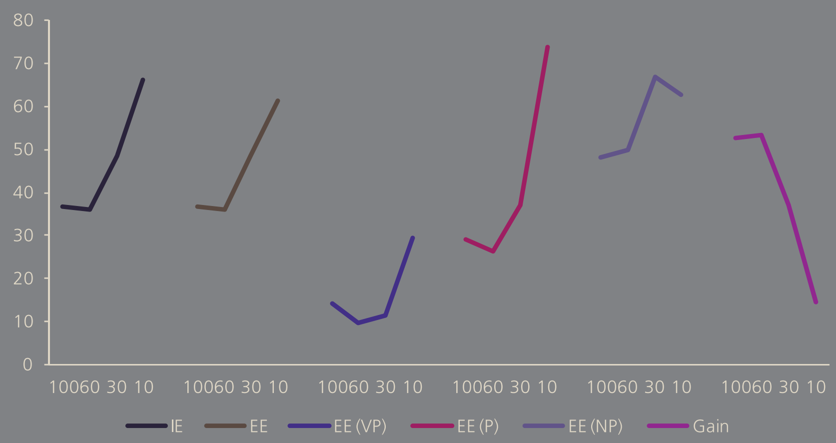
2. Targeting outcomes: IE – Inclusion error; EE – Exclusion error of very poor, poor and near poor; EE (VP) – Exclusion error of very poor only; EE (P) – Exclusion error of poor only; EE (NP) – Exclusion error of near-poor only; Gain – percent improvement over random targeting, out of a maximum of 100 percent (perfect targeting).

3. Poverty levels: 'Very poor' are those households beneath approximately 0.8x the poverty line; poor are those households below the poverty line (but not very poor when calculating the EE here); 'near-poor' are those households below 1.2x the poverty line (but not poor when calculating the EE here). The national poverty line was around Rp 200,000 per month in 2009.

The two sets of results suggest that using the poorest 60 percent or the full distribution for scoring models generally leads to the best targeting outcomes. Comparing the national and district level model results, using the poorest 60 percent of the distribution leads to the same or better results, especially for the very poor and poor. On the other hand, while using 30 or 10 percent leads to relatively little difference with the national model, it leads to markedly worse outcomes with the district models. This is likely due to rapidly falling sample sizes. When using a national model, even the poorest 10 percent represents a large sample (around 27,000 households). However, at the district level, total samples range from around 1,300 households down to less than 200 households (most of Eastern Indonesia). Consequently, taking only less than half of this sample for the scoring regression means using relatively few households to determine scoring weights, which are then applied to all households, with obvious model error.

…but using only poorer households in the scoring regression leads to considerably worse targeting outcomes if models are run at the district level.

Figure 10.4: Targeting Outcomes Using Different Consumption Distributions for District PMT Models



Source: Susenas 2009 and World Bank calculations
Notes: 1. Level of Model: 100, 60, 30 and 10 are the poorest percent of households which were included in the PMT consumption scoring regression sample. All regressions were run separate district level models.
2. Targeting outcomes: IE – Inclusion error; EE – Exclusion error of very poor, poor and near poor; EE (VP) – Exclusion error of very poor only; EE (P) – Exclusion error of poor only; EE (NP) – Exclusion error of near-poor only; Gain – percent improvement over random targeting, out of a maximum of 100 percent (perfect targeting).
3. Poverty levels: 'Very poor' are those households beneath approximately 0.8x the poverty line; 'poor' are those households below the poverty line (but not very poor when calculating the EE here); 'near-poor' are those households below 1.2x the poverty line (but not poor when calculating the EE here). The national poverty line was around Rp 200,000 per month in 2009.

Taken together, the disaggregation and distribution results suggest that district level models with scoring weights taken from a regression over the poorest 60 percent of households are generally best. The disaggregation results suggest distinctly better targeting outcomes using district level models. Whether the resources and time are available to run this many models needs to be assessed, but the smallest level of aggregation seems preferable, subject to a minimum sample size.[102] The distribution results see little difference in results for a national model, but distinctly different results at the district level, preferring the poorest 60 percent slightly over the whole distribution, especially for the poorest households, and rejecting the use of lower percentages. Together the two sets of results suggest the following approach to scoring regressions in Indonesia:

1. Use district level models run over the poorest 60 percent of the consumption distribution;
2. Unless the sample size is beneath a certain threshold, in which case use a district level model with the whole distribution;
3. Unless the sample size remains beneath a certain threshold, in which case use a provincial or provincial urban-rural model.[103]

However, further research is required. These recommendations are tentative for a number of reasons, and further research is required. First, the simulated program was targeted at the near-poor and below, or around the poorest quarter of Indonesia. Whether the results hold for more targeted programs aimed at only the very poor, or broader programs aimed at more than half the country, is unclear. Second, the scoring weights were used to create PMT scores for households within the same sample. Future research would benefit from using different surveys for scoring regressions and targeting simulations, reflecting the practice in reality. Third, the simulations presented used the quota method for determining program beneficiaries. As we will see later, this can have quite different results than if a strict threshold method is applied.

102 Further research is needed to determine when the sample size becomes too small and a higher level model is preferred. Such analysis would also benefit from applying model weights to different survey data than the regression scores come from, unlike the current research.

103 Provincial model targeting outcomes do not vary significantly between 30 and 100 percent.

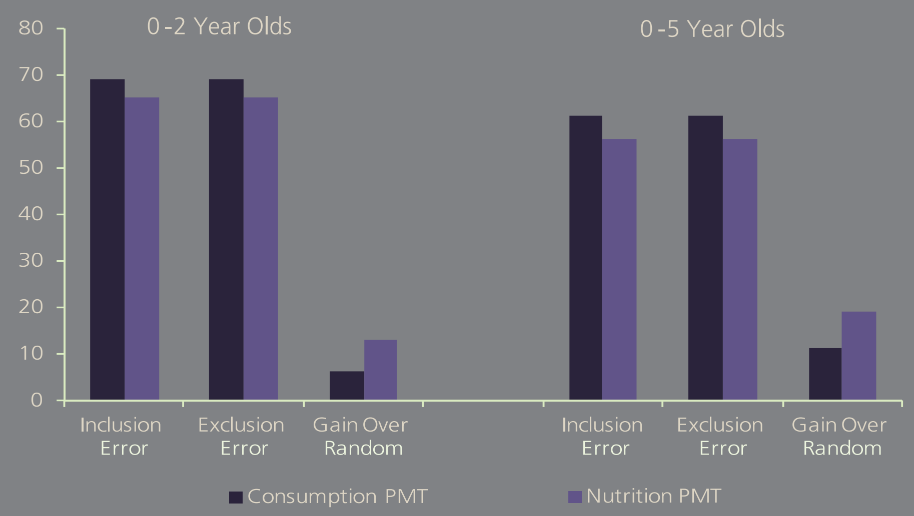
10.4 The Effect of Using a Malnutrition as a Dependent Variable

A broader question involves what variables programs should consider when using PMT. Are the usual variables of consumption or income the best, or should we consider other dependent variables? Poverty reduction and social assistance programs usually target the poor and vulnerable. In practice, policy makers use an economic proxy for living standards and poverty. However, is consumption, income or wealth the best monetary proxy? In the main report we saw that using wealth as a dependent variable may be better for estimating economic security, with consumption better suited for daily living standards. Furthermore, some targeted programs are aimed not at economic deprivation, but other indicators of under-development, such as malnutrition and non-enrolment, which are often linked to poverty but are distinct and not fully correlated.

The same set of PMT variables used in a consumption regression can be used to target malnutrition, with better targeting outcomes than consumption-based scoring, albeit results are far from satisfactory. We use two sets of PMT scores to target a malnutrition program. Both use the PMT variables, but while the first is a standard consumption-based regression, the second uses child weight-for-age z-scores – an indicator of child nutrition – as the dependent variable. We then determine beneficiaries based on their PMT scores, and compare this with an indicator for whether they are actually severely underweight (less than -2 standard deviations on the international distribution). As Figure 10.5 shows, targeting outcomes when PMT scores use nutrition as a dependent variable lead to lower errors and better improvements over random. However, the results are only slightly better and outcomes remain poor. This is not a surprising result, in that the PPLS08 PMT variables have been used, which were selected to predict consumption rather than nutrition, which are only partly correlated; a proper malnutrition PMT should include other variables, such as maternal height and health. However, it does demonstrate that using a non-economic dependent variable can allow you to better target non-economic program objectives.

The same set of PMT variables with different scoring weights can also be used to target malnutrition, with better targeting outcomes than consumption-based scoring, albeit still in need of improvement.

Figure 10.5: Targeting Outcomes for a Nutrition Program



Source: IFLS 2007 and World Bank calculations
Notes: Consumption PMT indicates PMT scoring coefficients were from per capita consumption regressed on PPLS08 specification. Nutrition PMT indicates a dummy variable for whether the household included a severely malnourished child was the dependent variable.

10.5 Using Thresholds and Quotas with PMT Scores to Determine Program Beneficiaries

Using PMT scores to determine program beneficiaries involves a key issue. How should the scores be used? Once variables have been collected and scored, the final step is using the PMT scores to determine program beneficiaries. Different approaches to using these scores leads to different households becoming beneficiaries and therefore different targeting outcomes. This raises the question of whether a strict score threshold should be used as a cut-off, or whether PMT scores should be used only as rankings, with a quota of beneficiaries from another source applied to this ranking.

Threshold and Quota Approaches

An obvious approach is to apply a strict poverty line-related threshold to PMT scores, and only households with lower scores enter the program. Since PMT scores are based on a consumption regression, they represent estimates of household per capita consumption. Many programs define target beneficiaries as those below a certain poverty line; in Indonesia major programs target the near-poor (those below about Rp 250,000 per person per day).[104] Consequently, beneficiaries can be determined as all households with a PMT score below the target consumption level. However, it is important to note that if a threshold is being set to be equivalent to an actual consumption level, certain adjustments need to be first be made. These are not discussed here (see World Bank 2012b for more details),[105] but have been made for all following results.

The threshold approach reduces the number of non-poor households receiving the program, but risks excluding poor households and including non-poor ones. Using a strict threshold minimizes the number of non-poor households who can enter the program, as those with PMT scores above this line do not enter the program. However, because PMT estimates include statistical error, excluding households above the threshold line could result in many target households having PMT scores above the eligibility threshold, and at the same time, non-target households having scores below it.

Program beneficiary numbers are often planned on the basis of local or national poverty rates. When a program defines target households as those beneath a certain level of income or consumption, then it can estimate the number of beneficiaries it should budget for from national household surveys, which can indicate poverty rates and how many households are below the target level. This provides more certainty for budgeting and operational planning purposes.

However, in cases where not all households have been surveyed by PMT, the number of beneficiaries identified as under the program threshold can be considerably lower than program targets. Much of the time, not all households in a population are surveyed with PMT for targeting purposes. Even within specific areas, it is very common for only some households to be surveyed. Even if PMT is completely accurate, then if a poor household is not surveyed, it will be excluded from the program. If PMT surveys exclude a considerable proportion of households, then even with an accurate model, the number of beneficiaries identified may be significantly lower than programs had planned and budgeted for, and communities and local government been expecting.

An alternative to using a threshold approach is to rank PMT scores, and households with the lowest scores up to the program quota enter the program. PMT scores can also be used solely to rank households, with no threshold applied. Instead, with program quotas being pre-determined from poverty mapping or national household surveys, the lowest ranking households by PMT score become program beneficiaries, up until the local program quota is filled. If all households have been surveyed with PMT, then the number and identity of beneficiaries under both threshold and quota approaches will be very similar, provided the threshold has been set correctly.[106] However, if not all households have been surveyed, results will differ.

The quota approach ensures that program beneficiary numbers are exactly as planned. It may also allow poor households above the threshold to enter the program, but risks including non-poor households. One advantage of the quota approach is that program beneficiary numbers can be met with reasonable precision, making program expenditures and planning more certain. In addition, while model error means poor households may have PMT scores

104 The pilot conditional cash transfer program, PKH, targets only the very poor, or those beneath about Rp 170,000 per day.

105 The threshold is only based on the targeted consumption eligibility level, and is not exactly the same. Since the PMT scores (predicted consumption) and consumption (actual) will have different distributions, the threshold needs to be adjusted to ensure the same eligibility rates in the population.

106 Again, see World Bank (2012b).

above the line used in the threshold approach, the quota approach can allow them to enter the program.[107] The concomitant risk is that if PMT models are less accurate, households with PMT scores indicating that they are above the line and not poor are included, because the there are not enough households with scores below the line to meet the quota.

The targeting outcomes will depend on the accuracy of the PMT model, and the proportion of target households surveyed by PMT. The targeting outcomes will be context specific. As discussed, if all households have been surveyed with PMT, then the targeting outcomes under both approaches will be very similar. However, usually for logistical and financial reasons, much less than all households are surveyed. In this case the quota and threshold targeting outcomes can diverge significantly. The outcomes depend on model fit and the number of target households missing from the PMT survey, as summarized in Table 10.1 below.

The targeting outcomes using threshold versus quota approaches will depend on the accuracy of the PMT model, and the proportion of target households surveyed by PMT.

Table 10.1: Differences in Threshold and Quota Approaches to PMT Scores When Not All Households are in PMT Database

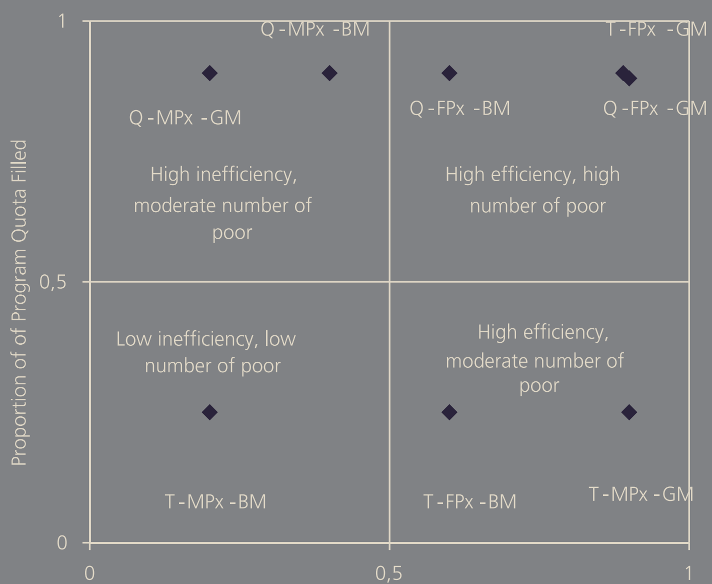
	Threshold Approach		Quota Approach	
	PMT threshold set in accordance with program eligibility criteria. All households with PMT score below threshold become beneficiaries.		Local program beneficiary quotas set in accordance program eligibility criteria and local poverty rates from geographical targeting or poverty maps. Households ranked by PMT scores, and lowest households up to program quota becomes beneficiaries.	
	Few Target Households Excluded from PMT Survey	**Many Target Households Excluded from PMT Survey**	**Few Target Households Excluded from PMT Survey**	**Many Target Households Excluded from PMT Survey**
Number of Beneficiaries Identified	Somewhat less than number of target households according to local poverty rates.	Considerably less than number of target households according to local poverty rates.	Exactly the number of target households according to local poverty rates.	Exactly the number of target households according to local poverty rates.
Targeting Accuracy: Model Fit Good	Low inclusion and exclusion error, as households with PMT scores above threshold more likely to be non-target, and those with scores below threshold more likely to be target. **Most of target households become beneficiaries. Few non-target households become beneficiaries.**	Low inclusion error, as households with scores above threshold more likely to be non-target. High exclusion error because many target households excluded from PMT survey. **Few target or non-target households become beneficiaries.**	Low inclusion and exclusion error, as households with lowest ranked PMT scores likely to be target and most target households are in survey, while households with higher scores and over the quota are likely to be non-target. **Most of target households become beneficiaries. Few non-target households become beneficiaries.**	High inclusion error and moderate exclusion error, as many target households excluded from PMT survey, so many low ranked households are non-target. However, a few target households who have scores above the threshold due to model error become beneficiaries. **Some target and non-target households become beneficiaries.**
Targeting Accuracy: Model Fit Poor	Moderate inclusion and exclusion error, as many target households have PMT scores above threshold, while many non-target households have scores below threshold. **Some target and non-target households become beneficiaries.**	Moderate inclusion and high exclusion error, as many non-target households have scores below threshold, while many target households on the PMT survey have scores above the threshold, and many target households with scores below threshold are not on survey. **Few target households become beneficiaries. Some non-target households become beneficiaries.**	Moderate inclusion and exclusion error, as some target households are ranked less deserving than some non-target households. However, many target households who have scores above the threshold due to model error become beneficiaries, replacing non-target households with scores below the threshold excluded from the survey. **Some target and non-target households become beneficiaries.**	High inclusion and exclusion error, as some target households are ranked less deserving than some non-target households. However, some target households who have scores above the threshold due to model error become beneficiaries, replacing non-target households with scores below the threshold excluded from the survey. **Some target and non-target households become beneficiaries.**

107 When not all households which would have had scores below the threshold have been surveyed, then households above the line which have been surveyed will replace them. Some of these could actually be poor but have a PMT score above the line because of model error.

The best approach will depend in part on accurately assessing these factors but also program and political objectives. Figure 10.6 shows how each scenario performs in terms of identifying sufficient number of beneficiaries and the proportion of beneficiaries identified who are target households. Selecting an approach therefore means estimating model accuracy (easily done) and how many target households have been excluded from the PMT survey (less easily done). In addition it means considering program and political objectives. Table 10.2 outlines the circumstances when a quota approach makes more sense, and when a threshold one does. If including as many poor households as possible is the most important factor, then the quota approach is preferred. If reducing inclusion error is most important, then a threshold approach is preferred if the model is accurate, but a quota approach may in fact be better for an inaccurate model. Finally, programs which provide benefits which are valued similarly by both poor and non-poor households maintain effectiveness when using a quota approach, even with mistargeting. However, programs with high marginal benefit to the poor but low marginal benefit to the rich may be better suited to a threshold approach, ensuring that money is not wasted on those who do not value the program.

The best approach will depend in part on assessing the accuracy of the PMT model, and the proportion of target households surveyed by PMT...

Figure 10.6: Proportion of Program Quota Filled versus Proportion of Beneficiaries Who are Target Households



Notes: Assumes Program Quotas are determined from poverty mapping or geographical targeting, based on local poverty rates. Q is quota approach, T is threshold approach, FPx is few poor excluded from PMT survey, MPx is many poor excluded from PMT survey, GM is good model fit, BM is bad model fit.

…and also program and political objectives.

Table 10.2: Appropriate Circumstances to Use Threshold and Quota Approaches

Threshold Approach	Quota Approach
▪ When inclusion error matters. ▪ When other methods for identifying missing quota are available. ▪ For programs whose benefits have high marginal value to target households (such as the very poor), but low marginal value to non-target households.	▪ When PMT model is not accurate. ▪ When exclusion error matters. ▪ When identifying a set number of beneficiaries is important (meeting program budgets). ▪ For programs whose benefits have high marginal value to both target and non-target households, such as health insurance where catastrophic shocks would hurt even non-poor households, thus providing significant benefit to inclusion error households

Applying Thresholds and Quotas in Indonesia

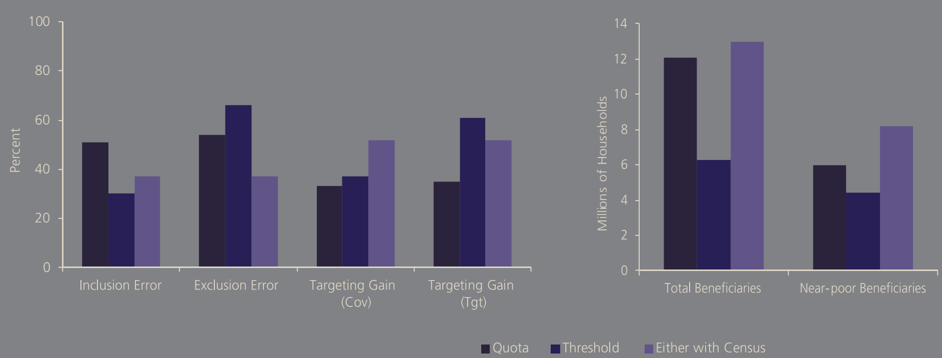
These considerations are made more explicit in an example from Indonesia, applying the quota and threshold approaches to determine beneficiaries for a simulated program. In this analysis we look to target a program which is aimed at the near-poor and below, which numbered 13 million households in 2009. We simulate a PMT survey of 16 million households, similar to the current BPS listing of the poor.[108] We then use both the quota and threshold approaches at the district level to determine program beneficiaries. The quota is the number of near-poor households in the district, while the threshold is the adjusted near-poor line in the district.[109] For the threshold approach, all households with PMT scores under the district threshold become beneficiaries, and no one else. For the quota approach, households with the lowest PMT scores are kept up until the district quota is reached. In some districts the number of households on the PMT list is less than the district quota (number of near-poor in the district), in which case the quota goes unfilled in that district.

There is a trade-off between targeting outcomes, total number of beneficiaries identified, and total number of poor beneficiaries identified. We measure performance on three dimensions. First we look at targeting outcomes, which means inclusion and exclusion error, and gain over random. Second we consider the total number of beneficiaries identified, compared to the actual number of near-poor households. Finally we check the total number of near-poor beneficiaries; target households who enter the program. The results are presented in Figure 10.7. The threshold approach has lower inclusion error and higher targeting gain at the target level than the quota approach. However, it has a higher exclusion error and half the number of total beneficiaries than the quota. When we take this much lower coverage for the threshold method into account, the targeting gain above random is very similar for both methods. The quota method reaches 6 million near-poor households, while the threshold method reaches only 4.4 million.

In this case, the threshold method maximizes proportion of benefits received by the near-poor, while the quota method maximizes the total benefits received by the near-poor. The threshold method is better if reducing inclusion error and maximizing the proportion of benefits that go to the near-poor is most important. The quota method is better if reducing exclusion error, reaching the highest number of near-poor, and meeting program quotas is most important. Thus there is a trade-off in this situation between targeting efficiency and total welfare improvement for the target population. These results, of course, are particular to the target level and PMT list used.

There is a trade-off between targeting outcomes, total number of beneficiaries identified, and total number of poor beneficiaries identified.

Figure 10.7: Outcomes of Applying the Threshold and Quota Approaches in Indonesia



Source: Susenas 2009 and World Bank calculations.
Notes: Target households are near-poor and below in each district. Inclusion and exclusion errors are calculated at target levels. Targeting gain over random is calculated at target levels (taking near-poor as population who should be receiving program) and coverage levels (taking total number of beneficiaries as the poorest population who should be covered).

108 We keep BLT recipients in Susenas as our survey listings. BLT recipients in 2008-09 have a very large overlap with the PSE05 PMT listing and the PPLS08 PMT listing. 16 million is under the 18.5 million on PPLS08 as not all households had information on the PMT variables.

109 We do not use the near-poor line itself. Since the actual consumption distribution and predicted (PMT) distribution are different, we get different near-poor rates if we apply the near-poor line directly to the predicted distribution. Instead we find the threshold on the predicted distribution that gives us the same near-poor rate as when the real near-poor line is applied to the actual distribution. This is discussed in World Bank (2012b).

11. Technical Annex 3: Constructing PSE05

11.1 Constructing the PSE05

Community leaders (usually the head of the neighbourhood) were asked for recommendations for poor households, which yielded about 16 million households (first phase of registry). All households were surveyed using PSE05 (*Pendataan Sosial Ekonomi Penduduk* 2005). The questionnaire included the variables used in the PMT scoring system.

Table 11.1: PSE05 Indicators

No.	Variable	Variable classification	
1	Floor area		
2	Floor type	1 = earth/bamboo/low quality wood	
		2 = cement/ceramic/high quality wood	
3	Wall type	1 = bamboo/grass/low quality wood	
		2 = concrete wall/high quality wood	
4	Toilet facility	1 = public/others	
		2 = own	
5	Drinking water source	1 = well or unprotected spring/river/rain/others	
		2 = mineral water/bottled/piped/pumped/well or protected spring water	
6	Source of lighting	1 = non electricity	
		2 = electricity (PLN/non-PLN)	
7	Fuel	1 = wood/charcoal	
		2 = Kerosene	
		3 = Gas/Electricity	
8	Frequency of buying beef/meat/milk in one week	1 = never bought	
		2 = one time	
		3 = two times/more	
9	Frequency of eating in one day	1 = one time	
		2 = two times	
		3 = three times/more	
10	Frequency of buying new clothes in one year	1 = never bought	
		2 = one time	
		3 = two times/more	
11	Ability to go to the doctor	1 = yes	2 = no
12	Sector of work of household head	1 = agriculture	6 = wholesale
		2 = plantation	7 = transportation
		3 = livestock	8 = services
		4 = fisheries	9 = others
		5 = industry	0 = not working
13	Highest education of household head	1 = elementary/below	
		2 = junior high	
		3 = senior high/above	

No.	Variable	Variable classification	
14	Asset		
	a. Savings	1 = yes	2 = no
	b. Gold	1 = yes	2 = no
	c. Color TV	1 = yes	2 = no
	d. Livestock	1 = yes	2 = no
	e. Motorcycle	1 = yes	2 = no

The 14 variables were reclassified as 1 or 0, with 1 being an indicator of poverty. The more indicators with 1 that a household has, the poorer that household is ranked. The reclassification proceeded as below.

Table 11.2: PSE05 Indicators Reclassified

No.	Variable	Score 1	Score 0
1	Floor area 1*	<= 8 m^2	> 8 m^2
	Floor area 2*	<= 10 m^2	> 10 m^2
	Floor area 3*	<= 15 m^2	> 15 m^2
2	Floor type	Earth	non-earth
3	Wall type	bamboo/others	concrete wall/wood
4	Toilet facility	public/others	own
5	Drinking water source	well or unprotected spring/ river/rain/others	mineral water/bottled/piped/pumped/well or protected spring water
6	Source of lighting	non electricity	electricity
7	Fuel 1*	wood/charcoal	kerosene, gas/electricity
	Fuel 2*	wood/charcoal, kerosene	gas/electricity
8	Frequency of buying beef/meat/milk in one week 1*	never bought	1 time, 2 times/more
	Frequency of buying beef/meat/milk in one week 2*	never bought, 1 time	2 times/more
9	Frequency of eating in one day 1*	1 time	2 times, 3 times/more
	Frequency of eating in one day 2*	1 or 2 times	3 times/more
10	Frequency of buying new clothes in one year 1*	never bought	1 time, 2 times/more
	Frequency of buying new clothes in one year 2*	never bought, 1 time	2 times/more
11	Ability to go to the doctor	No	yes
12	Sector of work of household head	agriculture	non-agriculture
13	Highest education of household head 1*	elementary	junior high, senior high
	Highest education of household head 2*	elementary, junior high	senior high
14	Asset	doesn’t have assets	has assets

Notes: The use of these variables depend on the results of a Tukey test in each district.

The characteristics of poor households are different from one district to another district, so the total number of poor households with a particular characteristic in a district is used as a weight in the scoring calculations. An example is given below.

Assume that the distribution of the poor household in each variable in a certain district is as below. Total number of poor household:

- whose floor area is below 8 m^2 is 1,000 households;
- who eat once a day is 500 households;
- who never bought clothes is 800 households;
- who cannot afford medical treatment is 500 households;
- whose floor type is earth is 1,000 households.

Then the weight for each variable is given by the total number of poor household with that variable divided by total number of poor household from all variables.

Table 11.3: PSE05 Indicator Weights

Variable	# of poor household	Weight
Floor area	1000	1000/3800 = 0.26
Frequency of eating	500	500/3800 = 0.13
Ability of buying clothes	800	800/3800 = 0.21
Ability of having a medical treatment	500	500/3800 = 0.13
Type of floor	1000	1000/3800 = 0.26
Total	3800	1.00

Using these weights, we can calculate the total score for each household. The higher the household score, the poorer it is considered. Households were then classified using the following cut-off points:

1. very poor if 0.8 <= score <= 1
2. poor if 0.6 <= score < 0.8
3. near poor if 0.2 <= score < 0.6
4. non-poor if score < 0.2

This scoring system generated around 15.5 million households.

The list of 15.5 million was submitted to PT Pos to produce KKB cards (Kartu Kompensasi BBM). Distribution was done by BPS door to door, at which time they also verified the household condition. By the time of the scheduled KKB delivery, it was already known that the government was initiating BLT, and consequently there were many protests from households who considered themselves poor and also wanted to receive BLT. The government then asked BPS to work with local governments to establish posts for a follow-up registry (second phase registry).

Households registered during the second phase were also surveyed using the PSE05 questionnaire. The total number of households from the first and second surveys was about 22 million households; thus there were about 6.5 million households in the second survey (22.0 - 15.5). All households in the second survey were ranked using a different scoring system, with about 3.5 million households being considered very poor, poor, or near poor.

The second scoring system did not use weights to calculate the household score, with cut-off points to determine the classifications as:

1. very poor if score = 14
2. poor if score = 12-13
3. near poor if score = 9-11
4. non-poor if score < 9

Approximately 19 million households were identified as beneficiaries from the first and the second phases.

11.2 Approximating the PSE05 with Susenas

Some PSE05 variables such as frequency of buying meat, eating, buying clothes, and the ability to afford medical treatment when someone in the household is sick are not in Susenas. BPS adjustments to obtain estimates of the PSE05 variables from Susenas questionnaire are as below.

Proxy for frequency of buying meat in one week
- frequency = never bought if:
  daging1 <= (mdaging1-(0.5*sdaging1))
- frequency = 1 time if:
  daging1 > (mdaging1-(0.5*sdaging1)) and
  daging1 < (mdaging1+(0.5*sdaging1))
- frequency = 2 times or more if:
  daging1>=(mdaging1+(0.5*sdaging1))
- where daging1 = weekly household expenditure on meat
  mdaging = average weekly household expenditure on meat in a district
  sdaging = standard deviation of weekly household expenditure on meat in a district

Proxy for frequency of eating in a day
- frequency = 1 if:
  food1 <= (mfood1-(0.5*sfood1))
- frequency = 2 if:
  food1 > (mfood1-(0.5*sfood1)) and food1 < (mfood1+(0.5*sfood1))
- frequency 3 or more if:
  food1 >= (mfood1+(0.5*sfood1))
- where food1 = weekly household expenditure on food
  mfood = average weekly household expenditure on food in a district
  sfood = standard deviation of weekly household expenditure on food in a district

Proxy for frequency of buying clothes in a year
- frequency = never bought if
  baju1 <= (mbaju1-(0.5*sbaju1))
- frequency = 1 if:
  baju1 > (mbaju1-(0.5*sbaju1)) and baju1 < (mbaju1+(0.5*sbaju1))
- frequency = 2 or more if:
  baju1 >= (mbaju1+(0.5*sbaju1))
- where baju1 = yearly household expenditure on clothes
  mbaju = average yearly household expenditure on clothes in a district
  sbaju = standard deviation of yearly household expenditure on clothes in a district

Proxy for ability to afford medical treatment when sick
- has ability if:
  sehat1 <= msehat1
- does not have ability if:
  sehat1 > msehat1
- where sehat1 = yearly household expenditure on health
  msehat = average yearly household expenditure on health in a district

12. Technical Annex 4: Constructing PPLS08

BPS created the PMT score using indicators found in Susenas and Podes. The PMT weights were calculated using stepwise regression for each of the kabupaten, therefore there will be different PMT weight for each kabupaten. The dependent variable for the PMT was the natural logarithm of the adjusted per capita expenditure, that is the per capita expenditures after adjustment for kabupaten-specific purchasing power. The indicators that were excluded from the stepwise regression were considered not significant and have a 0 score. The specification of indicators used from Susenas and Podes can be found below, some of them were reclassified as 1 or 0 and some of them not.

Table 12.1: Indicators from Susenas

No.	Variable
1	Type of place (1=Urban, 0=Others)
2	Per capita Floor
3	Type of Floor (1=Not earth, 0=Others)
4	Type of Wall (1=Brick/Cement, 0=Others)
5	Toilet Facility (1=Private, 0=Others)
6	Drinking Water source (1=Clean, 0=Other)
7	Electricity (1=PLN, 0=Others)
8	Type of Roof (1=Concrete/Corrugated, 0=Others)
9	Fuel for Cooking (1=Not Firewood, 0=Other)
10	Ownership of house (1=Private, 0=Others)
11	Having Micro Credit
12	Household Size
13	Household Size Squared
14	Age of the head of household
15	Age of the head of household Square
16	Head of household (1=Male, 0=Female)
17	Head of household is Married
18	Head of household is Male*Married
19	Sector of HH Head is Agriculture
20	Sector of HH Head is Industry
21	Sector of HH Head is Service
22	Sector of HH Head is in Formal Sector
23	Sector of HH Head is in Informal Sector
24	Education Attainment of HH Head is Elementary School
25	Education Attainment of HH Head is Junior School
26	Education Attainment of HH Head is Senior +
27	Number of children 0-4
28	Number of Children in Elementary School
29	Number of Children in Junior High School
30	Number of Children in Senior High School
31	Maximum Education Attainment within HH is Elementary School

No.	Variable
32	Maximum Education Attainment within HH is Junior School
33	Maximum Education Attainment within HH is Senior +
34	Dependency Ratio
35	Able to afford health care if sick (Puskesmas/Poliklinik)
36	Have Savings
37	Have Valuable Assets goods
38	Have Agricultural Land
39	Have Motocycle

Table 12.2: Indicators from Podes

No.	Variable
1	Population Density
2	Distance to District
3	Existence of SD (1=exist, 0=not exist)
4	Existence of SLTP (1=exist, 0=not exist)
5	Existence of Puskesmas/Pustu (1=exist, 0=not exist)
6	Existence of Polindes (1=exist, 0=not exist)
7	Existence of Posyandu (1=exist, 0=not exist)
8	Availability of Doctor (1=available, 0=not available)
9	Availability of Bidan (1=available, 0=not available)
10	Road type (1=asphalt, 0=others)
11	Existence of semi permanent market place (1=exist, 0=not exist)
12	Existing of Credit Facility (1=exist, 0=not exist)

The PSE05 list was updated by having communities remove households who had moved or all of whose members had died (in theory, households who were no longer poor should also have been removed, but this was seldom done in practice).

All updated households were surveyed using PPLS08 (*Pendataan Program Perlindungan Sosial 2008*). The questionnaire included the variables used in the PMT scoring system.

Table 12.3: PPLS Household Indicators

No.	Variable	Variable classification
1	Floor area	
2	Floor type	1 = earth/bamboo/low quality wood 2 = cement/ceramic/high quality wood
3	Wall type	1 = bamboo/grass/low quality wood 2 = concrete wall/high quality wood
4	Toilet facility	1 = public/others 2 = own
5	Drinking water source	1 = well or unprotected spring/river/rain/others 2 = mineral water/bottled/piped/pumped/well or protected spring water
6	Source of lighting	1 = non electricity 2 = electricity (PLN) 3 = electricity (non-PLN)
7	Fuel	1 = wood/charcoal 2 = Kerosene 3 = Gas/Electricity
8	Frequency of buying beef/meat/milk in one week	1 = never bought 2 = one time 3 = two times/more
9	Frequency of eating in one day	1 = one time 2 = two times 3 = three times/more
10	Frequency of buying new clothes in one year	1 = never bought 2 = one time 3 = two times/more
11	Ability to go to the doctor	1 = yes 2 = no
12	Asset	
	a. Savings	1 = yes 2 = no
	b. Gold	1 = yes 2 = no
	c. Color TV	1 = yes 2 = no
	d. Livestock	1 = yes 2 = no
	e. Motorcycle	1 = yes 2 = no
13	Accessed micro credit in past year	1 = yes 2 = no
14	Building ownership status	1 = own 2 = rent 3 = free rent
15	Type of roof	1 = low quality roof tiles/metal plates/asbestos or foliage/bamboo/others 2 = high quality roof tiles/concrete/metal plates/ asbestos
16	Have agricultural land	1 = yes 2 = no
17	if yes, total area of the agricultural land	
18	Often indebted for daily needs	1 = yes 2 = no

Table 12.4: PPLS Individual Indicators

No.	Variable	Variable classification
1	Gender	
2	Age	
3	Marital status	1 = single 3 = divorce 2 = married 4 = widow/er
4	Highest education attainment	1 = not attending school 2 = elementary/equal 3 = junior high/equal 4 = senior high/equal/above
5	Working	1 = yes 2 = no
6	Sector of work	1 = agriculture 6 = industry 2 = plantation 7 = construction 3 = livestock 8 = transportation 4 = fisheries 9 = wholesale and services 5 = mining 0 = others

All those variables were then reclassified/coded in accordance with the rules that have been defined in the PMT. BPS applied all the coded PPLS08 variables with the PMT weight for each kabupaten to get the final PMT score for each household. BPS calculated the predicted per capita expenditure for each household by applying the antilog of the final PMT score.

BPS created 3 types of poverty line to be used to determine the very poor, poor, and near poor from the predicted per capita expenditure from PPLS08.

a. BPS already has the food poverty line, non-food poverty line, and total poverty line for Susenas 2008 July.
b. The very poor lines were calculated as food poverty line + mean of 20% of housing expenditure + mean of clothing expenditure in each kabupaten.
c. The near poor line is poverty lines*1.2
6. BPS classified each household into one of the 4 category as below:
a. very poor if the per capita expenditure (pcexp) < very poor line
b. poor if very poor line ≤ pcexp < poverty line
c. near poor if poverty line ≤ pcexp < near poor line
d. non poor if pcexp ≥ near poor line

13. Data Annex

13.1 Average Per Capita Consumption by Decile and Province in Indonesia, 2007-10

Table 13.1: Average Monthly Per Capita Household Consumption (Rp.000s.) by Decile and Official Poverty Status, 2010

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
national	174	230	273	320	374	437	517	626	802	1,476	177	534
urban/rural												
urban	175	230	274	320	374	437	517	627	806	1,505	178	610
rural	174	231	272	320	373	437	517	625	797	1,385	176	458
region												
Sumatera	174	231	273	320	374	436	517	626	800	1,453	176	494
Jawa/Bali	176	230	273	320	374	437	517	625	802	1,491	178	539
Kalimantan	179	231	274	321	375	437	517	628	803	1,484	182	576
Sulawesi	175	231	272	318	374	437	517	630	807	1,434	177	605
NT	169	230	272	319	372	435	515	630	804	1,522	171	498
Maluku	171	228	274	321	373	439	516	625	811	1,224	173	488
Papua	154	227	271	319	374	437	514	635	798	1,315	155	520
province												
Aceh	168	231	274	319	371	436	511	625	795	1,260	170	415
Sumatra Utara	171	232	274	322	374	436	517	624	801	1,519	173	507
Sumatra Barat	176	233	272	319	373	435	516	624	799	1,336	178	516
Riau	174	231	272	321	374	436	517	628	808	1,340	178	519
Jambi	182	229	274	320	373	440	517	630	805	1,371	185	494
Sumatra Selatan	174	231	272	319	375	434	516	629	798	1,481	176	477
Bengkulu	178	233	273	321	376	441	521	619	794	1,422	180	503
Lampung	176	229	271	320	374	436	520	626	802	1,665	178	482
Bangka Belitung	178	230	276	323	372	435	518	631	790	1,379	182	510
Kepulauan Riau	183	230	273	317	377	439	513	625	789	1,280	184	512
DKI Jakarta	182	232	275	320	375	435	519	628	807	1,589	184	672
Jawa Barat	173	230	274	320	375	437	517	625	802	1,429	175	551
Jawa Tengah	177	230	272	319	373	437	517	623	799	1,469	180	480
DI Yogyakarta	174	231	275	321	372	436	515	627	812	1,495	176	583
Jawa Timur	176	230	274	319	373	437	515	625	798	1,418	179	478
Banten	180	231	273	323	374	436	517	624	805	1,669	182	679
Bali	179	231	274	318	372	438	520	632	813	1,419	181	650

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
Nusa Tenggara Barat	172	230	270	320	372	436	517	631	806	1,568	175	530
Nusa Tenggara Timur	167	230	274	318	371	435	512	628	800	1,452	168	463
Kalimantan Barat	183	231	274	323	373	435	518	626	809	1,514	184	553
Kalimantan Tengah	179	233	274	320	376	438	516	629	803	1,286	180	525
Kalimantan Selatan	181	232	273	319	374	438	518	628	799	1,494	184	608
Kalimantan Timur	173	229	276	323	376	439	518	631	801	1,529	177	611
Sulawesi Utara	182	231	273	320	375	436	516	629	813	1,384	185	586
Sulawesi Tengah	175	230	274	316	374	440	521	627	809	1,296	175	528
Sulawesi Selatan	174	231	271	317	373	436	518	632	808	1,443	177	640
Sulawesi Tenggara	172	231	270	319	377	438	515	633	799	1,491	172	612
Gorontalo	172	231	274	319	376	434	513	626	787	1,617	174	614
Sulawesi Barat	186	230	272	319	375	440	513	627	814	1,400	188	545
Maluku	169	228	275	321	372	439	514	617	791	1,193	172	435
Maluku Utara	178	229	272	320	374	438	517	632	831	1,239	179	548
Papua Barat	148	226	273	320	373	439	515	625	775	1,357	148	463
Papua	156	227	270	319	375	437	513	638	803	1,306	158	541
gender												
male	174	230	273	320	374	437	517	626	803	1,478	176	533
female	174	231	273	320	374	437	517	626	802	1,474	177	536
hh head gender												
male	174	231	273	320	374	437	517	626	802	1,479	177	534
Female	174	230	274	319	374	436	517	624	803	1,450	177	536

Table 13.2: Average Monthly Per Capita Household Consumption (Rp.000s.) by Decile and Official Poverty Status, 2009

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
national	160	213	250	0	326	371	427	508	648	1,234	165	463
urban/rural												
urban	159	213	251	287	326	372	428	508	650	1,266	165	531
rural	160	213	250	287	326	371	427	508	646	1,141	165	395
region												
Sumatera	160	214	250	287	325	371	427	507	648	1,125	164	431
Jawa/Bali	162	213	250	287	326	371	427	508	648	1,267	166	473
Kalimantan	162	214	252	286	326	371	427	512	648	1,203	167	503
Sulawesi	159	212	250	287	326	372	428	510	651	1,265	164	471
NT	154	212	251	287	325	369	431	507	647	1,254	160	415
Maluku	158	211	251	287	327	372	425	512	641	1,070	163	425
Papua	146	211	251	288	326	370	432	511	649	1,032	150	443
province												
Aceh	156	213	251	286	325	371	424	505	642	1,010	159	370
Sumatra Utara	161	214	250	287	326	371	430	506	654	1,085	167	438
Sumatra Barat	165	215	252	287	326	370	426	509	634	1,027	171	442
Riau	169	214	251	288	325	370	430	503	648	1,204	174	495
Jambi	160	212	251	285	326	371	425	507	640	998	169	421
Sumatra Selatan	158	214	250	285	324	372	425	507	653	1,151	163	406
Bengkulu	162	211	251	285	326	369	425	505	646	1,013	168	402
Lampung	157	214	250	288	324	371	423	511	653	1,301	161	418
Bangka Belitung	162	216	251	288	326	371	431	516	641	1,046	168	449
Kepulauan Riau	147	213	252	287	326	375	429	515	646	1,078	151	450
DKI Jakarta	163	215	251	286	328	372	430	506	647	1,312	169	609
Jawa Barat	162	213	251	287	327	371	428	509	648	1,371	168	497
Jawa Tengah	162	212	251	286	325	372	426	508	650	1,199	167	411
DI Yogyakarta	153	211	250	286	325	368	430	508	647	1,148	159	490
Jawa Timur	161	213	250	286	326	370	427	507	648	1,140	166	432
Banten	162	216	250	287	326	372	426	507	648	1,309	166	543
Bali	168	214	251	287	328	372	428	509	655	1,132	171	513
Nusa Tenggara Barat	150	212	251	287	324	371	431	508	650	1,252	155	425
Nusa Tenggara Timur	159	211	251	288	326	368	431	505	644	1,257	165	405
Kalimantan Barat	161	214	251	287	326	372	427	512	651	1,106	167	479
Kalimantan Tengah	166	215	251	285	326	371	430	514	643	1,098	171	462
Kalimantan Selatan	165	214	253	287	327	371	427	510	650	1,276	172	522
Kalimantan Timur	158	214	252	285	326	372	426	511	647	1,281	161	548
Sulawesi Utara	163	213	249	287	326	369	427	507	653	1,189	168	444
Sulawesi Tengah	151	212	249	287	326	371	430	511	641	1,100	157	445
Sulawesi Selatan	161	212	250	286	326	373	427	509	654	1,312	166	502

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
Sulawesi Tenggara	160	214	251	287	326	374	430	514	649	1,341	164	454
Gorontalo	158	209	250	288	322	369	424	514	656	1,327	164	439
Sulawesi Barat	163	212	251	287	328	367	429	513	651	1,070	168	420
Maluku	157	212	252	286	326	372	422	509	650	1,054	161	372
Maluku Utara	166	210	250	288	328	372	428	513	635	1,079	172	487
Papua Barat	142	210	250	289	325	373	433	500	657	1,150	146	411
Papua	148	211	251	287	326	369	431	513	647	1,010	152	454
gender												
male	160	213	250	287	326	371	427	508	648	1,242	165	462
female	160	213	251	287	326	371	427	509	649	1,226	165	464
hh head gender												
male	160	213	250	287	326	371	427	508	648	1,240	165	462
Female	161	213	251	287	326	371	429	508	650	1,186	166	473

Source: Susenas
Notes:
1. The table presents real per capita expenditures: they have been adjusted by for spatial differences in purchasing power using provincial urban/rural poverty lines as deflators and the national poverty line as a base.
2. National poverty line is Rp. 200,262.
3. Deciles are national household deciles (created nationally using household weights).
4. Average per capita expenditures were calculated using individual weights.

Table 13.3: Average Monthly Per Capita Household Consumption (Rp.000s.) by Decile and Official Poverty Status, 2008

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
national	0	190	223	260	298	340	393	469	0	1,108	150	419
urban/rural												
urban	143	190	223	260	298	341	394	470	602	1,131	150	477
rural	143	190	222	260	297	340	393	469	596	1,041	150	360
region												
Sumatera	142	190	223	259	297	340	393	469	598	1,065	150	396
Jawa/Bali	144	190	223	260	298	340	393	469	600	1,132	151	427
Kalimantan	146	190	223	260	298	340	394	467	599	1,106	154	448
Sulawesi	142	190	223	261	298	341	396	472	602	1,055	149	424
NT	142	190	221	260	298	339	392	468	603	1,028	148	369
Maluku	142	190	223	258	298	339	393	473	598	1,049	148	384
Papua	125	189	220	260	298	338	395	471	600	989	130	397
province												
Aceh	138	190	222	259	297	340	392	467	601	912	144	331
Sumatra Utara	144	191	223	259	298	341	393	467	594	1,104	151	397
Sumatra Barat	147	190	223	259	297	340	395	470	602	1,057	155	397
Riau	146	189	224	258	297	340	393	474	603	1,045	155	441
Jambi	145	191	223	261	298	342	393	466	586	998	152	408
Sumatra Selatan	142	188	222	259	297	338	393	472	600	984	150	376
Bengkulu	142	188	222	258	297	339	394	472	593	1,264	150	402
Lampung	142	190	224	260	298	342	391	464	605	1,132	149	400
Bangka Belitung	145	188	224	261	295	341	393	468	591	964	155	408
Kepulauan Riau	132	193	223	261	299	340	394	471	590	1,054	141	409
DKI Jakarta	147	192	224	261	299	341	394	469	602	1,267	152	561
Jawa Barat	144	189	223	261	297	339	392	470	600	1,149	152	443
Jawa Tengah	144	190	223	260	298	339	393	468	597	1,043	150	372
DI Yogyakarta	142	190	222	258	297	340	394	468	604	1,102	149	438
Jawa Timur	143	190	223	260	298	341	393	470	600	1,109	149	400
Banten	148	189	222	260	297	341	394	469	598	1,116	158	475
Bali	150	191	223	261	299	339	395	473	603	1,037	158	459
Nusa Tenggara Barat	142	190	222	261	297	339	392	468	603	1,065	148	382
Nusa Tenggara Timur	143	190	221	259	299	340	392	467	602	974	148	355
Kalimantan Barat	147	190	223	259	296	340	393	466	598	1,024	155	430
Kalimantan Tengah	145	189	224	261	299	340	394	467	598	1,000	152	433
Kalimantan Selatan	147	192	223	262	299	340	394	471	602	1,157	154	462
Kalimantan Timur	146	190	224	260	299	340	395	466	599	1,239	152	472

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
Sulawesi Utara	146	191	223	260	299	342	394	471	596	1,053	155	394
Sulawesi Tengah	138	191	223	260	298	341	397	473	603	997	145	396
Sulawesi Selatan	143	190	222	261	299	340	397	473	603	1,079	149	454
Sulawesi Tenggara	142	190	222	260	296	342	396	464	599	994	148	399
Gorontalo	141	186	222	258	297	339	395	472	613	1,115	149	403
Sulawesi Barat	145	187	222	262	298	343	391	474	598	1,024	154	397
Maluku	141	190	222	257	299	337	390	470	598	997	146	351
Maluku Utara	147	190	224	258	298	341	396	476	598	1,077	156	421
Papua Barat	129	189	220	263	295	336	391	468	604	968	135	344
Papua	124	189	220	260	299	339	396	472	599	992	129	415
gender												
male	143	190	223	260	297	340	393	469	600	1,100	150	417
female	143	190	223	260	298	340	393	469	600	1,115	150	421
hh head gender												
male	143	190	223	260	298	340	393	469	600	1,107	150	418
Female	142	190	223	260	298	340	394	469	600	1,114	149	428

Source: Susenas
Notes:
1. The table presents real per capita expenditures: they have been adjusted by for spatial differences in purchasing power using provincial urban/rural poverty lines as deflators and the national poverty line as a base.
2. National poverty line is Rp. 182,636.
3. Deciles are national household deciles (created nationally using household weights).
4. Average per capita expenditures were calculated using individual weights

Table 13.4: Average Monthly Per Capita Household Consumption (Rp.000s.) by Decile and Official Poverty Status, 2007

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
national	127	170	200	230	261	298	347	415	529	976	136	379
urban/rural												
urban	126	170	200	229	261	299	347	416	530	1,002	136	429
rural	128	169	200	230	261	298	346	414	527	906	136	327
region												
Sumatera	128	170	200	229	261	299	347	415	528	955	137	362
Jawa/Bali	127	170	200	230	261	298	347	416	528	991	136	385
Kalimantan	130	170	200	230	261	299	348	415	532	928	142	397
Sulawesi	128	170	200	230	261	298	348	415	531	979	136	393
NT	126	169	199	230	261	298	346	412	527	893	135	328
Maluku	125	168	200	229	262	298	346	413	533	979	133	351
Papua	114	169	200	227	261	297	349	414	532	927	120	372
province												
Aceh	125	169	199	229	260	299	345	414	525	806	133	298
Sumatra Utara	131	169	200	229	262	299	346	415	524	951	141	352
Sumatra Barat	133	171	200	230	260	299	347	414	531	911	141	368
Riau	123	170	200	229	261	298	347	414	528	964	134	407
Jambi	128	171	200	229	260	299	350	413	527	907	138	378
Sumatra Selatan	125	170	200	230	263	298	346	413	531	900	134	343
Bengkulu	129	170	200	230	260	299	346	412	533	973	137	346
Lampung	129	169	200	230	261	298	347	418	534	1,043	137	392
Bangka Belitung	128	171	199	227	261	298	348	416	526	930	137	351
Kepulauan Riau	127	170	200	229	262	301	346	414	527	970	137	363
DKI Jakarta	136	170	201	232	261	298	347	416	534	1,152	146	499
Jawa Barat	130	170	201	230	261	299	347	417	528	941	139	393
Jawa Tengah	127	170	199	229	261	297	345	414	528	998	135	342
DI Yogyakarta	124	170	200	228	260	298	347	415	528	964	133	388
Jawa Timur	126	169	200	230	260	298	347	416	528	972	135	358
Banten	128	170	199	230	260	298	347	416	531	1,005	141	431
Bali	131	170	200	230	262	299	348	418	525	965	142	437
Nusa Tenggara Barat	124	170	200	230	260	298	347	412	522	899	132	332
Nusa Tenggara Timur	129	168	198	230	261	298	344	411	534	887	138	323
Kalimantan Barat	132	170	200	230	261	300	347	414	533	870	142	368
Kalimantan Tengah	123	171	200	230	261	299	349	414	528	860	137	383
Kalimantan Selatan	136	169	202	229	261	299	349	415	530	964	147	428
Kalimantan Timur	130	170	199	230	262	299	346	415	536	994	139	415
Sulawesi Utara	130	170	200	230	261	301	348	416	523	976	139	395

Level	decile										poverty status	
	1	2	3	4	5	6	7	8	9	10	poor	not
Sulawesi Tengah	124	169	200	230	261	298	347	414	529	948	134	342
Sulawesi Selatan	130	171	200	230	260	298	348	415	534	979	137	415
Sulawesi Tenggara	127	171	202	230	262	298	350	417	529	939	134	382
Gorontalo	126	169	199	231	257	297	343	416	529	1,127	134	388
Sulawesi Barat	133	169	199	229	260	297	340	411	541	997	143	351
Maluku	125	169	200	230	262	298	347	412	536	1,016	132	313
Maluku Utara	124	168	201	228	262	298	345	414	532	960	135	393
Papua Barat	106	170	200	227	261	297	349	411	541	895	111	314
Papua	117	168	200	227	261	297	349	415	530	931	123	393
gender												
male	127	170	200	230	261	298	347	415	529	964	136	375
female	127	170	200	230	261	299	347	415	529	988	136	382
hh head gender												
male	127	170	200	230	261	298	347	415	529	976	136	379
Female	127	170	200	230	261	299	347	417	529	979	136	379

Source: Susenas
Notes:
1. The table presents real per capita expenditures: they have been adjusted by for spatial differences in purchasing power using provincial urban/rural poverty lines as deflators and the national poverty line as a base.
2. National poverty line is Rp. 166,697.
3. Deciles are national household deciles (created nationally using household weights).
4. Average per capita expenditures were calculated using individual weights.

13.2 Poverty by Province in Indonesia, 2007-10

Table 13.5: Poverty Rates at Different Poverty Lines by Province, 2010

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
national	13.3	12.4	23.8	34.5	44.9	10.8	10.0	20.0	30.0	40.0
urban/rural										
urban	9.9	9.0	17.7	27.2	37.0	8.0	7.4	14.8	23.5	32.5
rural	16.6	15.6	29.5	41.3	52.4	13.4	12.5	24.9	36.2	47.1
region										
Sumatera	13.3	12.4	24.2	35.7	46.5	10.5	9.8	19.9	30.2	40.5
Jawa/Bali	12.7	11.8	22.8	33.6	44.4	10.3	9.5	19.3	29.6	39.9
Kalimantan	7.4	6.9	16.2	25.9	36.0	5.4	5.0	12.5	21.1	30.5
Sulawesi	13.7	13.1	25.1	34.3	42.5	11.2	10.6	21.1	29.6	37.4
NT	22.3	21.1	36.7	47.0	57.2	19.1	18.1	32.6	42.8	52.9
Maluku	20.1	18.8	33.1	41.8	50.1	16.1	14.9	26.8	34.7	43.0
Papua	36.3	35.3	47.1	53.9	60.4	32.6	31.5	42.5	49.0	55.3
province										
Aceh	21.0	19.7	34.4	45.8	58.7	16.7	15.5	28.5	39.1	52.6
Sumatra Utara	11.3	10.5	21.1	32.6	44.0	8.5	7.9	16.5	26.5	37.1
Sumatra Barat	9.5	8.9	18.2	29.2	40.6	7.7	7.2	15.0	24.7	35.0
Riau	8.6	7.8	17.8	29.1	39.7	6.5	5.8	13.9	23.5	33.5
Jambi	8.3	7.5	18.5	30.9	40.9	6.2	5.8	14.6	25.9	35.2
Sumatra Selatan	15.5	14.6	28.4	40.7	50.6	12.7	11.9	24.4	35.7	45.3
Bengkulu	18.3	17.3	33.7	44.0	52.7	15.4	14.5	29.0	38.9	47.5
Lampung	18.9	17.6	31.8	43.5	54.0	15.6	14.6	26.9	38.2	48.9
Bangka Belitung	6.5	5.7	14.2	25.2	35.7	4.9	4.2	11.1	20.5	30.3
Kepulauan Riau	8.0	7.7	13.4	22.2	32.5	6.2	5.9	11.1	18.4	27.3
DKI Jakarta	3.5	3.1	7.4	15.5	26.0	2.6	2.3	5.6	12.6	22.0
Jawa Barat	11.3	10.6	19.9	30.7	41.4	8.7	8.2	16.4	26.5	36.7
Jawa Tengah	16.6	15.2	29.1	40.8	51.9	13.4	12.2	24.8	36.0	46.8
DI Yogyakarta	16.8	15.8	27.9	38.1	46.9	13.8	12.9	24.0	33.4	41.9
Jawa Timur	15.3	14.1	27.5	39.3	50.1	12.7	11.7	23.8	35.2	45.7
Banten	7.2	6.6	13.8	22.5	33.1	5.1	4.7	10.5	18.1	27.7
Bali	4.9	4.5	11.4	20.1	30.0	3.8	3.5	9.4	17.4	26.4
Nusa Tenggara Barat	21.6	20.0	35.1	45.2	54.8	19.0	17.7	32.0	42.1	51.5
Nusa Tenggara Timur	23.0	22.2	38.4	48.9	59.7	19.2	18.5	33.4	43.7	54.7
Kalimantan Barat	9.0	8.5	21.2	31.5	41.6	6.7	6.3	16.5	25.6	35.5
Kalimantan Tengah	6.8	6.6	15.4	25.6	36.6	5.2	5.0	11.9	21.3	31.4
Kalimantan selatan	5.2	4.8	12.3	22.3	33.2	3.9	3.6	10.0	18.7	28.2
Kalimantan Timur	7.7	6.9	13.6	21.6	30.4	5.6	5.0	10.5	17.6	25.7
Sulawesi Utara	9.1	8.2	20.5	32.7	42.4	7.3	6.6	17.1	27.7	36.1
Sulawesi Tengah	18.1	17.6	30.8	40.9	48.6	14.6	14.2	25.6	35.1	43.4
Sulawesi Selatan	11.6	10.8	21.3	29.4	37.6	9.5	8.8	17.9	25.3	32.8
Sulawesi Tenggara	17.1	17.0	30.8	39.4	47.1	14.1	14.0	26.5	34.2	41.7

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
Gorontalo	23.2	22.2	36.1	44.0	51.2	20.0	19.1	32.4	40.0	47.5
Sulawesi Barat	13.6	12.6	26.2	37.6	46.0	10.5	9.8	20.9	31.5	40.8
Maluku	27.7	25.7	44.6	53.5	62.3	22.5	20.7	36.8	45.3	54.2
Maluku Utara	9.4	9.1	16.9	25.3	33.0	6.9	6.7	12.5	19.5	27.1
Papua Barat	34.9	34.6	45.8	54.2	61.2	29.2	28.9	39.3	46.6	54.0
Papua	36.8	35.6	47.5	53.8	60.2	33.8	32.5	43.7	49.9	55.8
gender										
male	13.3	12.3	23.7	34.5	44.9					
female	13.4	12.5	23.9	34.5	45.0					
hh head gender										
male	13.4	12.5	24.0	34.6	45.2	11.0	10.2	20.5	30.5	40.6
female	12.7	11.8	22.4	33.4	43.3	9.5	8.8	17.4	27.2	36.6

Source: Susenas
Notes: 10% PL is a poverty line constructed to give the poorest 10% of households nationally by real per capita expenditure. Similarly for Poorest 20%, 30% and 40%.

Table 13.6: Poverty Rates at Different Poverty Lines by Province, 2009

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
national	13.3	12.4	23.8	34.5	44.9	10.8	10.0	20.0	30.0	40.0
urban/rural										
urban	10.7	9.2	17.6	26.1	34.8	8.6	7.4	14.5	22.3	30.4
rural	17.3	15.0	28.6	40.8	52.3	14.0	11.9	24.0	35.6	47.0
region										
Sumatera	13.9	12.1	23.2	34.1	45.3	11.1	9.6	19.3	29.4	40.1
Jawa/Bali	13.7	11.7	22.7	33.1	43.0	11.5	9.7	19.9	30.0	39.9
Kalimantan	7.5	6.4	15.0	23.7	33.1	5.8	4.9	12.0	20.0	28.6
Sulawesi	14.8	12.6	23.9	34.0	44.3	12.3	10.4	20.3	30.0	40.0
NT	23.0	20.0	34.6	47.5	57.7	19.5	16.8	30.5	42.9	53.4
Maluku	20.9	18.3	30.6	41.8	52.2	17.0	14.7	26.0	37.0	46.7
Papua	37.1	34.2	44.2	53.0	58.7	30.6	28.0	37.0	45.5	50.9
province										
Aceh	21.8	19.8	35.0	45.9	58.3	17.6	15.8	29.5	40.3	52.2
Sumatra Utara	11.5	9.7	20.3	30.6	42.0	8.6	7.2	15.8	25.1	35.7
Sumatra Barat	9.5	7.9	17.7	26.7	37.7	7.4	6.1	14.4	23.0	33.2
Riau	9.5	7.9	16.0	26.0	35.2	7.3	5.9	13.0	21.9	31.2
Jambi	8.8	6.7	15.3	26.1	38.0	6.8	5.2	12.0	21.8	33.1
Sumatra Selatan	16.3	14.4	26.6	39.5	49.7	12.6	11.1	22.2	33.6	43.8
Bengkulu	18.6	15.2	29.2	40.9	52.1	15.6	12.6	25.1	35.4	46.7
Lampung	20.2	18.3	31.7	43.9	56.2	17.7	15.8	28.5	40.8	52.7
Bangka Belitung	7.5	6.2	14.4	26.1	37.2	6.5	5.7	12.3	22.5	33.5
Kepulauan Riau	8.3	7.6	14.3	21.2	34.2	6.8	6.4	13.0	19.2	28.0
DKI Jakarta	3.6	3.0	7.8	13.6	22.4	2.8	2.3	6.0	11.0	18.8
Jawa Barat	12.0	10.1	20.1	29.4	39.3	9.6	8.0	17.1	26.2	35.7
Jawa Tengah	17.7	15.1	28.6	41.8	52.7	14.8	12.4	24.7	37.6	48.5
DI Yogyakarta	17.2	14.8	25.8	36.5	45.3	15.6	13.5	23.8	33.6	42.0
Jawa Timur	16.7	14.6	27.7	38.9	49.1	14.2	12.2	24.7	35.6	46.3
Banten	7.6	6.8	13.9	21.7	30.0	6.5	5.5	11.8	19.4	27.8
Bali	5.1	4.5	9.5	15.9	25.2	4.4	3.6	8.2	14.2	23.1
Nusa Tenggara Barat	22.8	20.2	34.3	46.6	57.0	19.6	17.3	30.4	42.3	53.0
Nusa Tenggara Timur	21.8	19.8	35.0	45.9	58.3	17.6	15.8	29.5	40.3	52.2
Kalimantan Barat	23.3	19.8	34.9	48.3	58.5	19.4	16.2	30.6	43.7	53.9
Kalimantan Tengah	9.3	7.9	17.7	26.1	36.6	7.0	5.9	13.5	21.4	30.6
Kalimantan selatan	7.0	5.8	15.8	26.0	35.1	5.7	4.7	13.7	23.8	33.1
Kalimantan Timur	5.1	4.0	11.6	20.3	30.3	4.1	3.2	9.3	16.6	25.6
Sulawesi Utara	7.7	7.2	14.3	22.2	29.4	6.3	5.8	11.9	19.1	25.8

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
Sulawesi Tengah	9.8	8.2	17.6	30.6	42.1	8.0	6.7	14.5	26.1	37.1
Sulawesi Selatan	19.0	16.3	28.8	38.2	47.3	15.3	13.0	24.2	33.6	42.4
Sulawesi Tenggara	12.3	10.4	21.2	30.2	40.3	10.1	8.5	17.8	26.4	36.0
Gorontalo	18.9	16.6	28.5	38.9	50.1	16.4	14.2	25.6	36.0	47.1
Sulawesi Barat	25.0	21.1	33.8	46.3	55.7	23.1	19.8	31.3	44.3	53.4
Maluku	15.3	13.1	26.2	38.0	48.9	12.5	10.8	21.5	31.9	42.9
Maluku Utara	28.2	25.3	40.8	54.0	65.2	23.0	20.1	34.6	47.7	58.3
Papua Barat	10.4	8.3	16.1	24.4	33.7	8.4	7.0	13.8	21.7	30.0
Papua	35.7	33.3	44.0	51.6	59.4	21.3	19.3	27.6	34.1	41.0
gender										
male	14.1	12.2	23.2	33.7	43.9					
female	14.2	12.2	23.3	33.7	43.9					
hh head gender										
male	14.1	12.2	23.3	33.9	44.1	11.9	10.1	20.3	30.6	40.6
female	14.6	12.7	23.0	32.1	42.3	10.8	9.2	18.0	26.5	36.5

Source: Susenas
Notes: 10% PL is a poverty line constructed to give the poorest 10% of households nationally by real per capita expenditure. Similarly for Poorest 20%, 30% and 40%.

Table 13.7: Poverty Rates at Different Poverty Lines by Province, 2008

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
national	15.4	12.3	23.5	34.1	44.4	12.7	10.0	20.0	30.0	40.0
urban/rural										
urban	11.7	9.3	18.0	27.0	35.5	9.5	7.5	15.1	23.2	31.3
rural	18.9	15.2	28.6	40.9	52.8	15.7	12.3	24.5	36.3	48.0
region										
Sumatera	15.1	11.8	23.5	34.4	45.3	12.2	9.5	19.6	29.6	40.0
Jawa/Bali	15.0	12.0	23.0	33.5	43.7	12.5	9.8	19.9	29.9	39.9
Kalimantan	9.2	7.0	15.1	24.8	34.1	7.2	5.5	12.3	20.9	29.3
Sulawesi	15.7	12.7	22.9	34.0	44.7	12.5	9.8	18.9	29.1	39.4
NT	24.7	20.6	35.3	47.9	58.3	20.5	16.8	30.6	42.9	53.2
Maluku	22.1	18.1	31.6	44.1	52.5	17.4	14.2	25.5	37.2	45.2
Papua	36.7	33.2	46.0	54.1	61.1	33.1	30.3	41.6	49.9	57.1
province										
Aceh	23.6	20.0	34.2	49.2	61.4	19.1	15.9	28.6	42.9	55.1
Sumatra Utara	12.5	9.8	21.3	31.5	42.9	9.6	7.4	17.0	25.8	36.5
Sumatra Barat	10.7	7.7	18.2	28.7	39.6	7.8	5.7	13.7	23.1	32.5
Riau	10.6	7.7	16.3	26.2	35.3	8.1	5.8	12.7	21.9	30.4
Jambi	9.3	7.2	16.6	26.3	37.4	7.6	5.7	14.0	22.9	33.6
Sumatra Selatan	17.6	13.8	26.5	37.9	50.0	14.6	11.3	22.3	33.0	44.9
Bengkulu	20.6	16.2	28.8	39.4	50.1	17.3	13.5	25.1	35.3	46.0
Lampung	21.0	16.7	30.7	42.2	52.0	18.2	14.3	27.2	38.2	47.8
Bangka Belitung	8.6	5.9	14.2	24.1	33.1	6.9	4.6	11.5	19.3	27.3
Kepulauan Riau	9.2	7.3	17.5	26.8	36.5	7.1	5.4	14.3	23.4	32.8
DKI Jakarta	4.3	3.6	7.3	14.7	22.0	3.2	2.6	5.9	12.4	19.3
Jawa Barat	13.0	9.9	20.4	30.5	39.9	10.7	8.0	17.4	26.7	35.9
Jawa Tengah	19.2	15.5	29.3	41.8	53.9	16.0	12.7	25.0	37.0	49.0
DI Yogyakarta	18.3	14.8	26.9	37.4	47.2	15.0	12.2	22.5	32.0	40.9
Jawa Timur	18.5	15.4	27.6	38.7	49.3	15.4	12.5	24.1	34.8	45.3
Banten	8.2	5.6	13.1	21.0	30.0	6.1	4.1	10.3	17.4	25.8
Bali	6.2	4.4	11.3	20.0	29.0	4.8	3.3	9.4	17.2	25.2
Nusa Tenggara Barat	23.8	19.5	33.7	45.8	56.4	20.1	16.2	29.8	41.6	52.1
Nusa Tenggara Timur	25.7	21.8	37.1	50.0	60.2	21.1	17.7	31.7	44.6	54.7
Kalimantan Barat	11.1	8.0	18.0	27.8	37.5	8.7	6.3	14.5	23.3	32.0
Kalimantan Tengah	8.7	6.8	14.8	24.4	34.4	7.0	5.3	12.3	21.3	29.9
Kalimantan selatan	6.5	5.1	12.3	22.2	31.6	5.0	3.8	10.0	18.9	27.6
Kalimantan Timur	9.5	7.8	14.3	23.3	31.6	7.9	6.4	11.8	19.3	26.7

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
Sulawesi Utara	10.1	7.2	17.8	28.6	41.2	8.3	5.8	14.2	23.8	36.2
Sulawesi Tengah	20.8	17.3	28.9	40.2	52.5	16.6	13.3	23.9	34.6	46.7
Sulawesi Selatan	13.3	11.0	19.7	30.4	40.0	10.4	8.4	16.1	25.9	34.9
Sulawesi Tenggara	19.5	16.4	27.9	39.5	50.3	16.4	13.3	23.9	35.4	45.8
Gorontalo	24.9	19.4	32.6	43.7	53.9	21.3	16.6	28.6	39.6	49.5
Sulawesi Barat	16.7	12.1	24.2	37.0	48.5	13.0	8.8	19.5	30.2	41.1
Maluku	29.7	25.1	39.9	52.8	61.1	23.3	19.6	32.9	45.8	54.5
Maluku Utara	11.3	8.2	19.7	31.9	40.3	8.8	6.3	14.9	24.9	31.9
Papua Barat	35.8	31.3	48.4	57.5	64.2	28.8	25.7	40.9	50.5	58.3
Papua	37.1	33.8	45.1	52.9	60.0	34.7	31.9	41.9	49.6	56.6
gender										
male	15.4	12.3	23.4	34.0	44.4					
female	15.5	12.3	23.6	34.3	44.5					
hh head gender										
male	15.4	12.3	23.4	34.2	44.5	12.8	10.1	20.2	30.3	40.4
female	15.6	12.4	23.8	34.0	44.1	11.8	9.1	18.8	28.1	37.7

Source: Susenas
Notes: 10% PL is a poverty line constructed to give the poorest 10% of households nationally by real per capita expenditure. Similarly for Poorest 20%, 30% and 40%.

Table 13.8: Poverty Rates at Different Poverty Lines by Province, 2007

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
national	16.6	12.1	23.2	33.7	43.9	13.9	10.0	20.0	30.0	40.0
urban/rural										
urban	12.5	9.1	17.8	26.4	35.5	10.6	7.7	15.3	23.5	32.2
rural	20.4	14.9	28.3	40.5	51.7	17.0	12.1	24.2	35.9	47.0
region										
Sumatera	16.5	11.8	23.3	33.9	44.4	13.6	9.7	19.9	29.7	39.8
Jawa/Bali	16.0	11.6	22.5	33.1	43.2	13.7	9.8	19.6	29.9	40.0
Kalimantan	10.4	6.5	16.1	24.4	34.2	8.0	5.0	12.7	20.0	28.9
Sulawesi	17.0	12.8	23.5	33.3	43.5	13.9	10.2	19.8	29.0	38.8
NT	26.2	19.2	35.6	48.9	58.4	21.5	15.6	30.4	43.2	53.0
Maluku	23.2	18.0	31.5	43.4	52.8	19.6	15.3	27.1	37.6	46.5
Papua	40.4	35.3	46.3	55.4	63.0	34.5	29.6	40.7	49.7	57.5
province										
Aceh	26.6	20.3	36.0	47.9	59.4	22.1	16.5	31.1	42.3	54.3
Sumatra Utara	13.9	9.0	21.2	31.9	43.5	11.0	7.1	17.4	26.9	37.5
Sumatra Barat	11.9	8.6	18.1	27.8	37.0	9.3	6.4	14.5	23.0	31.5
Riau	11.2	7.9	16.5	23.5	32.9	9.0	6.2	13.7	20.3	29.0
Jambi	10.2	7.1	15.3	24.7	33.6	8.5	5.6	13.0	22.0	30.4
Sumatra Selatan	19.1	14.4	26.6	38.9	50.1	16.3	12.3	23.2	34.4	45.5
Bengkulu	22.2	16.6	29.7	42.3	53.6	18.6	13.4	25.5	37.6	49.3
Lampung	22.2	16.4	28.9	39.3	49.0	19.1	13.8	25.7	36.4	46.5
Bangka Belitung	9.6	6.9	15.6	26.7	37.5	8.1	5.8	13.4	22.4	31.7
Kepulauan Riau	10.3	7.3	15.3	26.9	36.6	8.3	6.0	12.3	22.3	31.4
DKI Jakarta	4.6	2.8	7.6	14.2	21.0	3.5	2.0	5.8	11.4	17.8
Jawa Barat	13.5	9.4	20.1	30.0	40.0	11.2	7.6	16.9	26.2	36.0
Jawa Tengah	20.4	15.2	28.5	41.3	52.5	17.1	12.4	24.7	37.1	48.6
DI Yogyakarta	19.0	14.5	26.3	38.0	46.9	16.7	12.6	23.2	34.4	43.1
Jawa Timur	20.0	15.0	26.7	37.9	48.7	17.5	13.1	23.8	35.0	45.9
Banten	9.1	5.6	13.3	21.3	30.5	6.9	4.2	10.4	17.7	26.1
Bali	6.6	4.0	10.9	18.8	27.0	5.5	3.4	8.9	16.3	24.1
Nusa Tenggara Barat	25.0	19.3	35.1	47.2	56.6	20.9	16.0	30.3	42.5	52.5
Nusa Tenggara Timur	27.5	19.0	36.0	50.7	60.3	22.4	15.0	30.4	44.1	53.6
Kalimantan Barat	12.9	8.1	20.5	29.5	39.9	10.6	6.6	17.0	25.3	34.8
Kalimantan Tengah	9.4	6.0	14.8	24.2	34.2	6.9	4.4	11.5	19.3	28.3
Kalimantan selatan	7.0	3.8	11.1	18.9	28.7	5.4	2.9	8.7	15.3	24.0
Kalimantan Timur	11.1	7.6	16.1	23.0	31.7	8.4	5.8	12.6	18.7	27.0

Level	Population Beneath Poverty Line (%)					Households Beneath Poverty Line (%)				
	Official PL	10% PL	20% PL	30% PL	40% PL	Official PL	10% PL	20% PL	30% PL	40% PL
Sulawesi Utara	11.5	8.1	16.2	26.9	36.6	9.2	6.3	13.3	23.4	32.3
Sulawesi Tengah	22.5	16.6	30.5	42.3	52.1	19.2	14.2	26.7	38.5	48.0
Sulawesi Selatan	14.1	11.1	19.6	28.1	38.8	11.1	8.4	16.2	23.5	33.6
Sulawesi Tenggara	21.4	16.7	29.4	39.3	48.7	18.0	13.6	25.5	35.0	44.1
Gorontalo	27.2	20.7	35.7	46.8	57.0	23.0	17.0	31.2	43.3	54.5
Sulawesi Barat	19.0	11.8	28.4	39.4	50.4	15.9	9.9	24.0	35.2	46.0
Maluku	31.1	24.8	41.3	54.4	63.7	27.0	21.7	36.4	48.1	57.1
Maluku Utara	12.0	8.4	17.5	27.7	37.3	9.2	6.2	14.0	22.6	31.4
Papua Barat	39.4	35.2	47.2	58.9	66.3	34.3	30.0	43.0	53.9	62.2
Papua	40.8	35.3	46.0	54.1	61.8	34.6	29.4	40.0	48.3	55.8
gender										
male	16.6	12.1	23.3	33.9	44.2					
female	16.5	12.0	23.1	33.5	43.6					
hh head gender										
male	16.6	12.1	23.2	33.7	43.9	14.2	10.2	20.3	30.3	40.3
female	16.0	11.5	23.0	33.8	43.6	12.3	8.6	18.2	28.0	37.8

Source: Susenas
Notes: 10% PL is a poverty line constructed to give the poorest 10% of households nationally by real per capita expenditure. Similarly for Poorest 20%, 30% and 40%.

13.3 Urbanization and Female-headed Household Rates by Province in Indonesia, 2007-10

Table 13.9: Urbanization and Female-headed Household Rates by Province, 2010

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
national	112,429	120,332	48.3	51.7	28,641	30,103	48.8	51.2	15.2
urban/rural									
urban	112,429	0	100.0	0.0	28,641	0	100.0	0.0	16.0
rural	0	120,332	0.0	100.0	0	30,103	0.0	100.0	14.5
region									
Sumatera	19,570	30,452	39.1	60.9	4,625	7,211	39.1	60.9	14.1
Jawa/Bali	78,011	59,598	56.7	43.3	20,441	15,753	56.5	43.5	15.6
Kalimantan	5,567	8,271	40.2	59.8	1,357	1,995	40.5	59.5	12.9
Sulawesi	5,245	11,825	30.7	69.3	1,245	2,775	31.0	69.0	16.1
NT	2,754	6,333	30.3	69.7	681	1,483	31.5	68.5	20.0
Maluku	643	1,688	27.6	72.4	138	363	27.6	72.4	11.8
Papua	639	2,165	22.8	77.2	154	523	22.8	77.2	9.2
province									
Aceh	1,183	2,925	28.8	71.2	264	654	28.8	71.2	20.6
Sumatra Utara	6,077	7,103	46.1	53.9	1,390	1,625	46.1	53.9	14.9
Sumatra Barat	1,553	2,975	34.3	65.7	372	712	34.3	65.7	19.9
Riau	2,915	2,869	50.4	49.6	683	672	50.4	49.6	12.6
Jambi	939	1,959	32.4	67.6	229	478	32.4	67.6	13.7
Sumatra Selatan	2,817	4,462	38.7	61.3	660	1,044	38.7	61.3	12.3
Bengkulu	625	1,151	35.2	64.8	154	283	35.2	64.8	10.5
Lampung	2,110	5,705	27.0	73.0	518	1,402	27.0	73.0	10.8
Bangka Belitung	498	543	47.8	52.2	123	134	47.8	52.2	10.8
Kepulauan Riau	852	759	52.9	47.1	232	207	52.9	47.1	13.0
DKI Jakarta	8,968	0	100.0	0.0	2,243	0	100.0	0.0	16.3
Jawa Barat	24,917	17,459	58.8	41.2	6,519	4,568	58.8	41.2	13.5
Jawa Tengah	15,758	16,666	48.6	51.4	4,132	4,369	48.6	51.4	16.7
DI Yogyakarta	2,206	1,225	64.3	35.7	666	371	64.2	35.8	18.4
Jawa Timur	17,717	18,517	48.9	51.1	4,833	5,054	48.9	51.1	17.7
Banten	6,375	4,215	60.2	39.8	1,521	1,005	60.2	39.8	12.7
Bali	2,069	1,516	57.7	42.3	527	386	57.7	42.3	10.8
Nusa Tenggara Barat	1,962	2,721	41.9	58.1	511	709	41.9	58.1	22.6
Nusa Tenggara Timur	791	3,612	18.0	82.0	169	773	18.0	82.0	16.6
Kalimantan Barat	1,321	3,431	27.8	72.2	297	771	27.8	72.2	11.3

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
Kalimantan Tengah	824	1,600	34.0	66.0	204	396	34.0	66.0	9.0
Kalimantan selatan	1,449	2,041	41.5	58.5	383	541	41.5	58.5	18.2
Kalimantan Timur	1,973	1,199	62.2	37.8	473	287	62.2	37.8	11.6
Sulawesi Utara	985	1,285	43.4	56.6	262	342	43.4	56.6	13.1
Sulawesi Tengah	552	2,076	21.0	79.0	132	494	21.0	79.0	13.1
Sulawesi Selatan	2,536	5,339	32.2	67.8	580	1,220	32.2	67.8	18.2
Sulawesi Tenggara	540	1,809	23.0	77.0	121	403	23.0	77.0	16.5
Gorontalo	283	622	31.3	68.7	72	159	31.2	68.8	12.7
Sulawesi Barat	348	693	33.4	66.6	78	157	33.4	66.6	18.2
Maluku	356	1,009	26.1	73.9	77	218	26.1	73.9	12.5
Maluku Utara	287	680	29.7	70.3	61	145	29.8	70.2	10.7
Papua Barat	167	567	22.8	77.2	41	138	22.8	77.2	9.2
Papua	472	1,598	22.8	77.2	114	385	22.8	77.2	9.1
gender									
male	55,835	60,162	48.1	51.9					
female	56,594	60,170	48.5	51.5					
hh head gender									
male	99,080	108,407	47.8	52.2	24,053	25,750	48.3	51.7	0.0
female	13,349	11,925	52.8	47.2	4,588	4,353	51.3	48.7	100.0

Source: Susenas

Table 13.10: Urbanization and Female-headed Household Rates by Province, 2009

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
national	112,429	120,332	48.3	51.7	28,641	30,103	48.8	51.2	14.5
urban/rural									
urban	111,081	0	100.0	0.0	24,486	0	100.0	0.0	15.5
rural	0	118,878	0.0	100.0	0	33,563	0.0	100.0	13.8
region									
Sumatera	19,241	30,001	39.1	60.9	3,873	7,773	33.3	66.7	13.5
Jawa/Bali	77,221	59,048	56.7	43.3	17,519	18,332	48.9	51.1	14.7
Kalimantan	5,456	8,117	40.2	59.8	1,160	2,128	35.3	64.7	11.9
Sulawesi	5,190	11,687	30.8	69.2	1,049	2,925	26.4	73.6	15.7
NT	2,714	6,246	30.3	69.7	562	1,570	26.4	73.6	19.7
Maluku	632	1,660	27.6	72.4	121	372	24.6	75.4	10.4
Papua	626	2,119	22.8	77.2	201	461	30.4	69.6	9.7
province									
Aceh	1,180	2,916	28.8	71.2	237	677	25.9	74.1	20.0
Sumatra Utara	6,008	7,023	46.1	53.9	1,221	1,758	41.0	59.0	14.7
Sumatra Barat	1,544	2,957	34.3	65.7	310	769	28.8	71.2	19.1
Riau	2,806	2,761	50.4	49.6	456	847	35.0	65.0	9.9
Jambi	923	1,925	32.4	67.6	189	507	27.2	72.8	13.5
Sumatra Selatan	2,775	4,397	38.7	61.3	559	1,120	33.3	66.7	12.4
Bengkulu	614	1,130	35.2	64.8	87	341	20.3	79.7	8.8
Lampung	2,081	5,626	27.0	73.0	406	1,488	21.4	78.6	10.1
Bangka Belitung	491	536	47.8	52.2	76	177	30.1	69.9	10.5
Kepulauan Riau	820	731	52.9	47.1	332	90	78.7	21.3	14.8
DKI Jakarta	8,917	0	100.0	0.0	2,230	0	100.0	0.0	15.8
Jawa Barat	24,506	17,171	58.8	41.2	5,437	5,471	49.8	50.2	12.8
Jawa Tengah	15,708	16,612	48.6	51.4	3,353	5,118	39.6	60.4	15.4
DI Yogyakarta	2,186	1,214	64.3	35.7	555	474	53.9	46.1	17.2
Jawa Timur	17,651	18,448	48.9	51.1	4,214	5,640	42.8	57.2	16.8
Banten	6,209	4,105	60.2	39.8	1,280	1,180	52.0	48.0	12.2
Bali	2,045	1,498	57.7	42.3	452	449	50.2	49.8	9.8
Nusa Tenggara Barat	1,933	2,681	41.9	58.1	414	787	34.5	65.5	22.4
Nusa Tenggara Timur	781	3,565	18.0	82.0	148	783	15.9	84.1	16.3
Kalimantan Barat	1,300	3,377	27.8	72.2	283	768	26.9	73.1	10.2
Kalimantan Tengah	804	1,560	34.0	66.0	144	441	24.6	75.4	9.2
Kalimantan selatan	1,426	2,010	41.5	58.5	320	591	35.1	64.9	17.1
Kalimantan Timur	1,925	1,170	62.2	37.8	414	328	55.8	44.2	10.3
Sulawesi Utara	974	1,270	43.4	56.6	185	412	31.0	69.0	12.2
Sulawesi Tengah	542	2,038	21.0	79.0	117	498	19.0	81.0	12.6

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
Sulawesi Selatan	2,520	5,306	32.2	67.8	561	1,228	31.4	68.6	17.9
Sulawesi Tenggara	528	1,766	23.0	77.0	93	419	18.2	81.8	16.5
Gorontalo	281	617	31.3	68.7	55	174	24.1	75.9	11.6
Sulawesi Barat	346	689	33.4	66.6	37	196	16.0	84.0	18.0
Maluku	351	995	26.1	73.9	79	212	27.1	72.9	10.9
Maluku Utara	281	665	29.7	70.3	42	160	21.0	79.0	9.7
Papua Barat	164	555	22.8	77.2	80	95	45.9	54.1	8.4
Papua	462	1,564	22.8	77.2	121	367	24.8	75.2	10.1
gender									
male	55,210	59,524	48.1	51.9					
female	55,871	59,355	48.5	51.5					
hh head gender									
male	98,311	107,548	47.8	52.2	20,700	28,945	41.7	58.3	0.0
female	12,769	11,330	53.0	47.0	3,786	4,618	45.0	55.0	100.0

Source: Susenas

Table 13.11: Urbanization and Female-headed Household Rates by Province, 2008

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
national	109,560	117,133	48.3	51.7	27,736	30,035	48.0	52.0	13.5
urban/rural									
urban	109,560	0	100.0	0.0	27,736	0	100.0	0.0	14.2
rural	0	117,133	0.0	100.0	0	30,035	0.0	100.0	12.9
region									
Sumatera	18,876	29,418	39.1	60.9	4,463	7,075	38.7	61.3	12.2
Jawa/Bali	76,338	58,430	56.6	43.4	19,820	16,000	55.3	44.7	13.9
Kalimantan	5,336	7,922	40.2	59.8	1,313	1,952	40.2	59.8	11.2
Sulawesi	5,119	11,512	30.8	69.2	1,209	2,705	30.9	69.1	14.3
NT	2,672	6,153	30.3	69.7	664	1,479	31.0	69.0	18.7
Maluku	621	1,629	27.6	72.4	132	324	28.9	71.1	9.5
Papua	598	2,068	22.4	77.6	134	500	21.1	78.9	8.4
province									
Aceh	1,175	2,881	29.0	71.0	280	687	28.9	71.1	18.5
Sumatra Utara	5,930	6,930	46.1	53.9	1,348	1,613	45.5	54.5	13.2
Sumatra Barat	1,534	2,937	34.3	65.7	383	688	35.8	64.2	17.7
Riau	2,687	2,645	50.4	49.6	633	608	51.0	49.0	9.2
Jambi	905	1,889	32.4	67.6	225	473	32.3	67.7	12.4
Sumatra Selatan	2,728	4,266	39.0	61.0	663	1,029	39.2	60.8	10.3
Bengkulu	600	1,106	35.2	64.8	141	272	34.2	65.8	8.8
Lampung	2,049	5,537	27.0	73.0	481	1,405	25.5	74.5	9.2
Bangka Belitung	483	528	47.8	52.2	120	128	48.5	51.5	9.2
Kepulauan Riau	785	700	52.9	47.1	189	172	52.3	47.7	11.0
DKI Jakarta	8,851	0	100.0	0.0	2,160	0	100.0	0.0	14.3
Jawa Barat	24,057	16,856	58.8	41.2	6,064	4,675	56.5	43.5	11.7
Jawa Tengah	15,646	16,544	48.6	51.4	4,187	4,561	47.9	52.1	14.9
DI Yogyakarta	2,163	1,201	64.3	35.7	710	349	67.0	33.0	17.3
Jawa Timur	17,573	18,364	48.9	51.1	4,715	5,090	48.1	51.9	16.0
Banten	6,031	3,987	60.2	39.8	1,442	944	60.4	39.6	11.5
Bali	2,017	1,477	57.7	42.3	542	380	58.8	41.2	9.9
Nusa Tenggara Barat	1,902	2,638	41.9	58.1	506	732	40.9	59.1	21.5
Nusa Tenggara Timur	770	3,515	18.0	82.0	158	747	17.5	82.5	14.8
Kalimantan Barat	1,278	3,325	27.8	72.2	284	773	26.8	73.2	9.9
Kalimantan Tengah	781	1,515	34.0	66.0	203	389	34.3	65.7	9.0
Kalimantan selatan	1,403	1,944	41.9	58.1	374	522	41.7	58.3	16.2
Kalimantan Timur	1,874	1,138	62.2	37.8	453	268	62.8	37.2	8.6
Sulawesi Utara	961	1,253	43.4	56.6	259	325	44.4	55.6	11.3

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
Sulawesi Tengah	531	1,999	21.0	79.0	125	479	20.7	79.3	12.2
Sulawesi Selatan	2,492	5,247	32.2	67.8	571	1,234	31.6	68.4	15.2
Sulawesi Tenggara	514	1,720	23.0	77.0	114	376	23.3	76.7	16.8
Gorontalo	279	612	31.3	68.7	66	142	31.6	68.4	11.8
Sulawesi Barat	342	681	33.4	66.6	75	149	33.3	66.7	17.2
Maluku	344	975	26.1	73.9	72	197	26.7	73.3	9.9
Maluku Utara	277	654	29.7	70.3	60	127	32.2	67.8	8.8
Papua Barat	147	542	21.4	78.6	32	135	19.0	81.0	9.1
Papua	451	1,526	22.8	77.2	102	366	21.8	78.2	8.1
gender									
male	54,446	58,692	48.1	51.9					
female	55,113	58,441	48.5	51.5					
hh head gender									
male	98,272	106,859	47.9	52.1	23,800	26,150	47.6	52.4	0.0
female	11,288	10,274	52.4	47.6	3,936	3,886	50.3	49.7	100.0

Source: Susenas

Table 13.12: Urbanization and Female-headed Household Rates by Province, 2007

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
national	108,318	115,911	48.3	51.7	25,910	28,613	47.5	52.5	13.5
urban/rural									
urban	108,318	0	100.0	0.0	25,910	0	100.0	0.0	13.8
rural	0	115,911	0.0	100.0	0	28,613	0.0	100.0	13.3
region									
Sumatera	18,577	29,088	39.0	61.0	4,123	6,699	38.1	61.9	12.9
Jawa/Bali	75,607	57,946	56.6	43.4	18,546	15,306	54.8	45.2	13.8
Kalimantan	5,234	7,811	40.1	59.9	1,234	1,839	40.2	59.8	10.4
Sulawesi	5,055	11,357	30.8	69.2	1,140	2,594	30.5	69.5	15.2
NT	2,636	6,077	30.2	69.8	609	1,391	30.5	69.5	17.9
Maluku	612	1,606	27.6	72.4	124	317	28.2	71.8	8.9
Papua	598	2,027	22.8	77.2	133	468	22.2	77.8	6.6
province									
Aceh	1,170	2,896	28.8	71.2	256	649	28.3	71.7	18.3
Sumatra Utara	5,867	6,855	46.1	53.9	1,297	1,489	46.5	53.5	14.9
Sumatra Barat	1,526	2,925	34.3	65.7	354	669	34.6	65.4	19.6
Riau	2,586	2,543	50.4	49.6	558	572	49.4	50.6	9.1
Jambi	889	1,857	32.4	67.6	196	431	31.2	68.8	12.1
Sumatra Selatan	2,690	4,261	38.7	61.3	580	987	37.0	63.0	10.8
Bengkulu	589	1,087	35.2	64.8	137	254	35.1	64.9	11.6
Lampung	2,021	5,465	27.0	73.0	443	1,363	24.5	75.5	9.1
Bangka Belitung	477	521	47.8	52.2	118	122	49.2	50.8	10.4
Kepulauan Riau	762	679	52.9	47.1	184	162	53.2	46.8	9.0
DKI Jakarta	8,804	0	100.0	0.0	2,025	0	100.0	0.0	13.6
Jawa Barat	23,683	16,599	58.8	41.2	5,705	4,375	56.6	43.4	12.3
Jawa Tengah	15,593	16,502	48.6	51.4	3,930	4,404	47.2	52.8	14.6
DI Yogyakarta	2,144	1,191	64.3	35.7	592	332	64.0	36.0	17.8
Jawa Timur	17,510	18,305	48.9	51.1	4,508	4,963	47.6	52.4	15.8
Banten	5,880	3,887	60.2	39.8	1,295	862	60.0	40.0	8.8
Bali	1,993	1,462	57.7	42.3	491	370	57.1	42.9	9.1
Nusa Tenggara Barat	1,874	2,601	41.9	58.1	460	688	40.1	59.9	20.3
Nusa Tenggara Timur	761	3,476	18.0	82.0	149	703	17.5	82.5	14.6
Kalimantan Barat	1,258	3,268	27.8	72.2	265	720	26.9	73.1	10.0
Kalimantan Tengah	762	1,481	34.0	66.0	186	350	34.7	65.3	8.2
Kalimantan selatan	1,383	1,951	41.5	58.5	353	507	41.1	58.9	14.1
Kalimantan Timur	1,830	1,112	62.2	37.8	430	263	62.1	37.9	8.0
Sulawesi Utara	950	1,239	43.4	56.6	242	334	42.0	58.0	12.2

Level	Population in Urban and Rural Areas (000s)				Households Beneath Poverty Line (%)				% female headed hh
	Urban	Rural	% Urban	% Rural	Urban	Rural	% Urban	% Rural	
Sulawesi Tengah	522	1,963	21.0	79.0	124	451	21.6	78.4	12.2
Sulawesi Selatan	2,471	5,205	32.2	67.8	534	1,152	31.7	68.3	17.5
Sulawesi Tenggara	502	1,679	23.0	77.0	112	365	23.4	76.6	14.5
Gorontalo	277	607	31.3	68.7	63	145	30.2	69.8	11.8
Sulawesi Barat	333	665	33.4	66.6	65	148	30.7	69.3	18.9
Maluku	339	960	26.1	73.9	69	190	26.5	73.5	10.2
Maluku Utara	273	645	29.7	70.3	56	127	30.6	69.4	6.9
Papua Barat	154	524	22.8	77.2	32	125	20.2	79.8	8.1
Papua	444	1,503	22.8	77.2	102	343	22.9	77.1	6.0
gender									
male	53,626	58,097	48.0	52.0					
female	54,692	57,815	48.6	51.4					
hh head gender									
male	96,977	105,101	48.0	52.0	22,337	24,800	47.4	52.6	0.0
female	11,341	10,810	51.2	48.8	3,573	3,813	48.4	51.6	100.0

Source: Susenas

13.4 Indonesian Targeting Outcomes by Province, 2007-10: Program Coverage by Decile

Table 13.13: Raskin Coverage by Decile and Province, 2010

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	75.7	72.0	66.4	60.8	53.4	50.4	41.9	34.2	23.4	8.3	48.7	20.5
urban/rural												
urban	77.1	69.7	59.3	53.6	42.5	37.5	27.0	20.8	13.6	3.3	35.5	15.2
rural	75.0	73.4	71.6	66.5	62.4	61.8	56.1	48.9	38.9	23.3	61.2	25.6
region												
Sumatera	63.8	56.6	50.7	46.0	38.6	35.6	30.7	23.1	14.9	5.1	37.4	20.4
Jawa/Bali	83.8	80.2	74.0	68.4	60.7	57.1	47.1	38.8	25.8	8.5	54.4	19.9
Kalimantan	54.5	51.8	44.8	39.6	35.3	33.1	26.7	23.3	16.0	6.8	29.9	12.9
Sulawesi	63.7	56.4	49.2	43.8	43.4	43.3	32.0	31.9	24.1	8.1	37.3	21.6
NT	82.1	82.0	82.7	74.3	66.3	66.2	65.5	59.3	44.3	20.7	68.2	33.5
Maluku	69.3	51.4	56.6	45.0	48.5	51.9	44.6	35.4	29.1	12.1	46.1	27.2
Papua	42.4	57.4	58.8	51.5	50.4	42.2	40.1	28.5	18.6	18.9	40.9	43.0
province												
Aceh	79.4	77.4	66.8	62.0	57.4	56.6	43.3	44.0	23.6	14.6	59.5	28.9
Sumatra Utara	54.9	47.2	42.6	37.0	30.6	27.8	18.3	17.8	9.8	3.6	28.5	17.1
Sumatra Barat	63.8	64.6	44.4	44.2	39.4	31.1	31.1	18.8	10.2	1.6	32.9	15.6
Riau	50.4	43.6	45.0	41.5	29.9	27.8	22.5	19.7	8.6	4.1	27.4	14.4
Jambi	46.4	48.7	42.7	29.9	32.9	27.1	21.7	13.0	9.4	7.9	27.1	15.0
Sumatra Selatan	54.3	53.3	51.8	44.5	34.9	35.3	31.1	18.4	17.8	6.2	37.0	24.7
Bengkulu	63.7	46.2	48.8	49.0	32.6	33.3	36.8	21.0	17.3	9.0	38.1	29.3
Lampung	78.9	71.4	66.8	65.9	65.9	59.0	57.8	46.7	32.1	9.2	59.8	27.6
Bangka Belitung	0.0	4.2	8.5	6.7	3.1	0.0	0.9	2.4	2.3	0.0	2.8	11.6
Kepulauan Riau	64.8	53.7	60.3	39.8	29.6	31.4	36.1	20.5	19.2	3.1	32.7	11.7
DKI Jakarta	39.7	40.6	28.4	23.1	17.8	13.3	11.3	6.5	4.9	1.0	12.7	5.9
Jawa Barat	80.5	78.5	75.6	73.2	63.7	60.4	49.5	42.2	28.7	7.4	54.2	16.8
Jawa Tengah	92.5	88.8	85.5	83.1	75.3	71.4	64.8	55.8	39.0	18.8	71.3	25.5
DI Yogyakarta	79.9	70.1	61.9	54.6	40.6	45.5	34.8	28.7	11.0	1.8	41.8	24.5
Jawa Timur	84.2	80.3	76.0	68.5	61.9	58.5	45.9	37.4	23.4	11.8	58.7	24.5
Banten	57.0	64.4	49.6	45.7	39.0	43.3	35.4	26.0	18.1	3.3	32.1	10.7
Bali	70.3	55.5	49.0	34.8	38.5	36.2	28.8	27.2	22.4	7.8	30.3	9.9
Nusa Tenggara Barat	96.2	95.1	95.2	90.5	83.3	84.6	78.2	70.8	54.0	26.5	80.4	33.1
Nusa Tenggara Timur	64.6	65.7	67.0	56.5	48.8	45.8	50.0	38.3	28.7	10.2	52.3	34.0
Kalimantan Barat	65.1	61.2	54.0	53.7	49.8	57.3	40.7	38.8	24.6	12.5	44.1	16.9
Kalimantan Tengah	66.4	53.6	48.9	37.4	32.7	28.2	25.0	19.7	19.2	7.2	30.5	12.1

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Kalimantan Selatan	44.4	41.5	37.8	30.2	28.3	25.5	24.0	18.7	13.4	5.3	23.2	10.4
Kalimantan Timur	35.2	39.8	34.1	31.1	25.9	16.8	12.0	11.2	7.8	1.8	17.8	11.0
Sulawesi Utara	63.8	56.3	36.7	49.0	48.1	47.4	36.2	33.1	21.5	6.6	36.0	17.8
Sulawesi Tengah	75.4	67.6	52.5	47.1	44.3	36.5	31.2	24.1	18.6	6.2	41.8	26.0
Sulawesi Selatan	48.7	42.2	41.9	31.0	34.8	37.3	22.9	29.6	23.4	7.7	29.0	18.3
Sulawesi Tenggara	76.8	73.8	67.7	57.3	60.9	58.0	56.6	46.5	35.1	12.7	52.7	26.9
Gorontalo	69.8	61.6	54.2	53.1	48.8	59.4	31.0	32.9	33.4	3.8	46.0	32.7
Sulawesi Barat	67.5	66.6	78.5	71.2	57.3	54.7	43.2	35.6	20.5	12.9	50.1	21.5
Maluku	70.5	53.6	54.9	54.0	55.1	55.0	51.2	45.0	36.9	5.6	52.6	37.2
Maluku Utara	63.8	42.7	59.6	29.8	42.6	48.4	39.6	26.0	20.4	16.1	36.7	12.9
Papua Barat	63.0	54.7	69.3	75.5	50.6	46.9	38.3	46.6	28.7	13.2	52.2	39.9
Papua	35.8	58.4	54.4	40.7	50.3	40.2	40.9	23.3	15.8	20.5	36.8	44.1
gender												
male	74.7	69.9	64.1	57.9	50.3	46.1	38.4	30.7	20.0	7.6	48.4	24.3
female	74.8	70.3	64.2	58.1	50.9	47.5	38.4	30.6	20.4	6.8	48.6	24.5
hh head gender												
male	75.3	71.4	65.4	59.0	51.2	48.6	39.2	32.0	21.6	8.2	47.5	21.0
Female	78.5	76.2	72.1	71.6	65.6	60.5	55.9	45.6	33.1	8.8	55.2	17.9

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.14: Raskin Coverage by Decile and Province, 2009

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	65.8	61.9	57.9	52.9	48.3	41.8	36.5	29.2	19.0	8.7	42.2	22.2
urban/rural												
urban	66.6	59.8	51.7	46.7	39.2	31.3	25.4	17.8	9.4	3.1	29.7	16.2
rural	65.5	62.9	60.9	56.2	53.4	49.1	45.1	39.7	31.7	21.0	51.3	26.5
region												
Sumatera	51.1	47.3	42.3	39.8	32.9	26.6	23.6	19.5	10.6	5.3	30.2	21.5
Jawa/Bali	74.6	70.1	66.8	60.0	56.1	48.8	42.5	33.8	22.1	9.8	48.4	22.2
Kalimantan	46.9	35.9	32.7	30.9	27.5	25.3	24.2	18.6	13.0	5.5	22.9	13.5
Sulawesi	40.5	37.1	34.8	36.6	30.2	31.9	26.4	19.0	13.8	5.5	27.5	22.4
NT	77.7	76.9	69.2	72.3	68.6	63.0	53.8	49.9	35.1	24.6	63.3	32.7
Maluku	53.5	50.6	50.4	49.0	46.0	45.8	47.2	39.8	27.9	9.0	43.2	28.4
Papua	43.8	45.7	40.1	46.6	50.1	34.4	33.4	29.0	20.9	7.0	36.1	38.7
province												
Aceh	60.4	66.1	65.0	59.7	59.2	47.2	37.9	32.8	19.9	8.6	51.3	31.6
Sumatra Utara	50.4	45.0	35.0	33.0	26.3	22.3	20.2	16.6	5.8	4.5	24.8	17.8
Sumatra Barat	71.0	57.1	49.9	42.4	32.3	30.2	21.2	14.2	8.9	4.9	29.9	15.6
Riau	69.6	66.0	60.7	53.5	48.9	31.8	32.5	21.4	11.1	4.4	35.1	14.5
Jambi	33.4	38.2	34.3	32.7	23.9	19.1	17.4	16.7	13.8	3.6	22.4	14.2
Sumatra Selatan	28.8	21.7	21.6	21.9	15.5	14.0	12.4	13.7	8.0	2.6	16.9	25.1
Bengkulu	15.3	23.0	20.1	27.4	18.2	4.9	11.6	13.6	5.7	3.5	15.5	27.1
Lampung	62.2	60.2	57.9	55.5	49.7	45.8	39.4	43.1	24.0	13.2	48.9	31.8
Bangka Belitung	12.2	6.9	3.0	11.3	4.4	4.3	0.0	4.8	3.7	1.3	5.0	14.0
Kepulauan Riau	52.1	37.3	37.4	27.5	25.3	18.4	21.2	11.3	5.5	3.4	20.2	13.9
DKI Jakarta	34.8	35.7	27.2	22.7	19.7	10.9	6.6	7.0	4.5	0.5	10.5	7.0
Jawa Barat	80.1	72.8	70.1	62.6	60.4	51.2	45.1	38.0	25.6	9.7	49.7	19.0
Jawa Tengah	88.3	84.2	82.3	79.5	74.2	71.3	61.8	50.2	36.4	21.8	69.3	27.6
DI Yogyakarta	70.0	67.4	57.4	53.6	41.8	38.6	32.2	25.7	15.9	3.3	39.9	26.6
Jawa Timur	66.6	64.5	60.8	55.9	53.0	48.9	44.4	34.9	20.3	11.6	48.4	27.4
Banten	26.2	28.0	28.7	20.8	23.2	17.5	16.3	12.2	11.7	3.1	16.7	13.2
Bali	60.2	49.9	44.1	42.4	31.0	21.6	19.8	17.3	13.2	8.4	24.6	9.4
Nusa Tenggara Barat	87.8	90.0	85.4	85.1	83.9	79.7	68.0	64.8	49.6	29.6	76.2	32.5
Nusa Tenggara Timur	64.0	61.3	50.2	55.0	49.7	44.2	32.0	30.1	16.5	17.4	46.6	33.1
Kalimantan Barat	52.3	38.6	29.7	34.7	34.7	28.1	34.3	21.2	21.2	7.4	27.7	15.3
Kalimantan Tengah	48.0	51.0	45.5	38.4	26.1	30.7	27.3	25.5	13.5	4.9	29.2	15.3
Kalimantan Selatan	27.9	14.2	24.1	22.0	19.1	19.6	16.8	14.8	9.6	2.7	15.2	10.4
Kalimantan Timur	51.5	40.0	34.1	30.3	29.7	25.0	17.2	13.5	6.2	6.8	20.7	13.2

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Sulawesi Utara	59.3	55.8	48.0	51.1	38.4	39.0	35.2	26.7	19.9	9.4	37.6	16.8
Sulawesi Tengah	41.9	43.8	35.2	36.0	33.0	27.2	28.8	16.2	13.5	11.7	29.2	26.1
Sulawesi Selatan	36.8	27.5	26.3	26.8	22.8	30.2	20.6	17.3	10.5	2.3	21.2	19.8
Sulawesi Tenggara	29.3	30.5	37.3	36.6	27.9	21.3	23.5	12.5	15.4	7.5	25.3	27.5
Gorontalo	40.4	47.7	34.2	43.3	33.2	43.9	29.7	23.5	7.3	0.0	33.0	34.4
Sulawesi Barat	60.5	52.3	45.8	61.4	62.4	51.1	39.5	30.5	25.1	16.8	45.3	23.5
Maluku	62.3	58.2	57.8	58.2	52.1	48.1	42.2	48.0	26.4	4.2	50.5	37.1
Maluku Utara	17.1	27.4	32.8	32.0	35.4	43.3	52.6	37.4	29.0	12.7	32.7	15.8
Papua Barat	64.6	48.8	55.6	42.7	64.4	45.6	46.0	28.5	27.9	9.8	45.3	28.7
Papua	39.2	44.7	36.1	48.6	43.5	26.0	25.6	29.2	18.0	6.1	32.8	42.3
gender												
male	64.3	60.3	55.0	49.9	43.6	37.2	31.4	24.7	15.3	6.7	40.5	25.5
female	65.0	60.0	55.1	49.7	44.5	37.9	31.9	24.6	15.3	6.7	40.6	25.6
hh head gender												
male	65.3	61.3	57.2	52.2	46.8	39.4	34.8	27.3	18.0	8.1	41.3	22.6
Female	69.3	66.1	63.0	57.5	57.6	56.0	45.9	40.0	24.9	11.5	47.6	19.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.15: Raskin Coverage by Decile and Province, 2008

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	75.6	70.6	66.0	59.9	57.5	47.2	40.0	32.5	21.9	9.2	48.0	24.1
urban/rural												
urban	75.1	65.2	57.5	49.4	45.4	35.9	27.3	20.8	11.9	3.7	34.0	18.2
rural	76.0	73.7	71.4	66.6	65.8	57.5	52.7	46.8	38.3	24.7	61.0	29.5
region												
Sumatera	65.4	56.9	52.5	46.6	43.8	35.1	30.6	22.4	16.2	8.6	38.2	23.6
Jawa/Bali	85.3	79.1	74.4	67.7	65.6	53.0	44.7	36.8	24.0	9.2	53.8	23.9
Kalimantan	56.1	51.7	44.2	37.3	37.0	34.9	27.8	24.1	19.2	9.4	30.8	15.5
Sulawesi	54.5	47.8	48.2	43.0	43.7	36.0	32.9	24.1	16.7	6.5	34.7	23.3
NT	72.6	74.6	70.3	71.7	66.5	64.6	60.7	53.4	37.8	22.9	63.1	36.3
Maluku	48.9	29.5	31.6	33.3	25.7	30.1	30.3	24.2	17.6	9.0	29.4	30.1
Papua	33.5	52.1	56.6	44.6	38.1	35.2	30.6	27.2	25.3	9.7	35.5	45.7
province												
Aceh	88.7	84.3	82.1	68.0	74.0	63.5	56.0	47.6	29.8	27.3	68.9	34.3
Sumatra Utara	58.5	45.6	37.2	37.5	29.3	25.3	23.4	14.1	11.4	5.3	27.9	20.6
Sumatra Barat	43.9	51.8	50.1	37.9	40.5	29.3	24.7	14.1	8.4	3.9	29.0	17.4
Riau	48.4	45.7	40.8	37.2	35.0	22.6	24.8	16.4	8.8	1.6	25.0	16.4
Jambi	67.6	57.7	42.0	44.5	30.3	22.2	20.1	20.7	17.1	6.5	30.1	17.6
Sumatra Selatan	58.7	55.0	49.9	44.8	48.9	38.9	37.2	26.4	26.9	17.1	42.0	26.6
Bengkulu	58.0	44.9	46.9	52.7	33.8	29.6	26.7	16.2	9.5	7.0	35.0	29.8
Lampung	76.8	70.0	68.9	65.5	66.1	57.5	49.6	41.8	28.4	13.6	57.3	31.5
Bangka Belitung	26.9	26.1	18.9	19.9	12.0	8.0	7.1	5.3	2.0	2.3	10.6	13.8
Kepulauan Riau	36.8	41.4	56.1	34.0	48.4	40.3	27.6	22.8	26.8	13.2	33.8	18.4
DKI Jakarta	44.1	34.3	22.8	20.4	19.8	17.3	12.1	7.9	5.1	1.0	12.2	8.0
Jawa Barat	83.5	76.2	75.3	66.6	68.2	54.2	49.1	40.0	25.7	8.4	52.6	21.1
Jawa Tengah	92.1	86.2	84.1	79.0	77.3	68.3	60.1	51.4	38.3	18.6	70.0	30.0
DI Yogyakarta	84.0	77.5	71.0	62.8	53.1	42.3	34.7	24.6	13.1	1.6	44.6	27.0
Jawa Timur	86.2	83.0	79.1	72.4	69.5	58.1	50.5	42.3	30.1	12.3	61.2	28.4
Banten	45.3	46.5	38.2	37.4	35.7	23.4	13.2	9.8	5.7	2.6	20.7	13.6
Bali	58.3	60.5	39.1	41.9	41.5	32.3	25.8	23.1	11.1	5.8	28.0	12.3
Nusa Tenggara Barat	98.1	98.3	95.1	96.4	91.3	85.3	82.2	73.9	46.4	32.7	84.3	34.9
Nusa Tenggara Timur	40.6	43.0	39.4	36.4	34.5	30.5	33.0	21.6	25.9	6.8	34.0	38.3
Kalimantan Barat	64.8	63.3	54.0	46.9	46.0	43.6	32.0	31.9	26.1	17.2	40.0	18.1
Kalimantan Tengah	73.4	62.3	56.0	46.0	37.0	44.2	41.3	29.4	25.2	9.6	38.5	15.3
Kalimantan Selatan	47.2	41.4	33.4	32.8	38.6	26.9	24.9	22.7	16.8	5.7	25.8	13.4
Kalimantan Timur	38.3	29.9	31.2	19.3	20.1	24.9	15.9	11.1	8.1	3.3	17.4	14.6

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Sulawesi Utara	71.3	53.0	55.8	39.1	39.9	28.7	34.4	20.2	8.7	7.7	34.3	17.8
Sulawesi Tengah	76.4	66.3	68.2	60.0	56.2	45.7	29.9	27.9	21.2	9.7	48.5	27.8
Sulawesi Selatan	40.8	35.8	39.1	34.2	40.2	31.7	32.2	24.0	17.6	5.2	28.3	20.8
Sulawesi Tenggara	43.5	42.3	35.6	40.6	44.6	34.4	30.7	27.8	17.6	8.9	33.2	28.8
Gorontalo	60.3	61.6	61.2	50.9	45.3	41.4	41.2	14.8	12.7	2.9	43.0	33.5
Sulawesi Barat	67.7	55.4	61.0	60.7	49.0	60.1	42.6	26.5	18.8	6.6	45.7	24.0
Maluku	54.7	34.7	37.3	39.1	30.6	32.6	36.3	24.2	24.4	5.2	35.9	38.4
Maluku Utara	22.8	17.9	20.9	23.1	19.7	26.4	24.5	24.3	13.0	11.5	19.9	18.1
Papua Barat	46.7	54.4	69.0	46.6	36.5	45.0	52.1	34.2	30.2	0.0	45.4	45.9
Papua	29.8	50.8	51.0	43.8	38.7	28.4	23.7	24.8	23.9	11.4	32.0	45.6
gender												
male	73.8	68.6	63.3	56.7	53.3	43.8	36.2	29.3	18.9	8.2	47.4	27.7
female	74.3	68.7	63.5	57.3	54.5	43.3	36.0	28.6	19.0	8.2	47.5	27.9
hh head gender												
male	74.8	70.0	65.2	58.4	55.5	45.0	37.8	30.8	20.8	8.6	46.9	24.3
Female	81.4	74.9	71.3	70.4	70.6	60.8	53.8	43.3	28.7	12.6	55.2	22.5

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.16: Raskin Coverage by Decile and Province, 2007

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	76.4	70.6	65.8	58.3	53.9	48.4	39.9	31.0	21.7	9.5	47.6	25.0
urban/rural												
urban	74.8	64.8	58.4	47.0	41.8	34.1	26.2	17.0	10.1	3.3	33.0	19.4
rural	77.4	74.0	70.5	66.3	62.9	60.2	53.4	46.9	38.8	25.3	60.8	30.1
region												
Sumatera	68.6	60.6	55.5	47.4	42.8	38.9	31.2	23.3	16.5	8.5	39.6	24.9
Jawa/Bali	83.7	76.4	70.6	63.8	59.5	53.2	43.6	33.7	23.3	9.4	51.7	24.8
Kalimantan	53.8	51.2	44.1	39.6	36.6	33.6	27.4	22.7	16.7	7.7	29.9	16.2
Sulawesi	63.3	60.9	58.0	47.1	41.9	37.5	33.2	27.0	17.9	7.3	38.4	24.3
NT	84.4	81.3	79.2	78.6	77.8	72.3	70.1	62.8	48.9	32.2	72.5	36.9
Maluku	45.6	46.3	45.9	40.4	37.5	33.0	28.3	24.0	15.8	7.6	34.1	32.5
Papua	31.2	44.1	45.1	39.0	31.7	41.3	33.4	33.4	22.0	15.1	33.5	45.1
province												
Aceh	88.0	82.6	78.5	71.5	62.1	64.4	60.8	53.6	32.6	27.6	69.0	37.4
Sumatra Utara	66.7	50.3	46.9	35.9	36.9	32.5	24.0	17.0	12.0	4.4	31.8	22.2
Sumatra Barat	50.0	42.7	42.4	31.6	34.8	24.6	21.0	13.2	5.2	3.5	24.2	18.9
Riau	45.0	57.3	51.9	34.9	21.6	27.6	20.5	19.0	11.3	6.0	25.7	17.0
Jambi	64.6	53.8	40.1	44.9	36.8	39.3	30.3	17.6	12.8	11.8	32.6	17.5
Sumatra Selatan	65.4	58.1	54.9	52.3	41.4	39.0	33.8	24.9	25.7	12.9	43.1	29.1
Bengkulu	62.1	58.5	48.6	45.1	49.0	29.9	33.9	29.4	14.7	6.2	40.9	32.0
Lampung	78.2	76.4	71.6	69.7	64.1	64.5	50.7	39.6	31.1	13.1	58.3	30.9
Bangka Belitung	19.4	19.8	27.2	13.9	18.7	15.2	10.1	7.8	2.8	2.5	13.2	18.5
Kepulauan Riau	55.9	61.9	60.6	29.7	38.7	32.7	24.4	20.7	23.1	7.1	33.3	17.1
DKI Jakarta	48.3	31.5	30.6	23.1	21.1	17.4	12.3	10.5	5.6	1.5	13.4	8.7
Jawa Barat	84.9	76.9	71.6	65.1	61.6	55.6	47.6	33.6	25.2	9.8	50.7	21.1
Jawa Tengah	92.8	89.3	84.6	75.4	75.0	67.5	58.8	49.9	37.1	16.6	69.4	31.3
DI Yogyakarta	84.5	73.3	73.0	65.3	57.6	44.8	36.2	30.0	21.4	3.7	49.2	29.1
Jawa Timur	78.4	71.0	64.7	61.3	54.8	52.6	43.0	35.0	22.1	11.0	52.4	29.5
Banten	68.0	48.2	48.4	44.2	42.4	34.0	27.5	20.5	15.0	3.6	29.5	13.7
Bali	57.2	61.9	49.3	49.8	50.5	38.2	34.3	26.0	14.6	7.7	32.5	12.8
Nusa Tenggara Barat	97.6	97.3	95.2	92.2	88.0	80.0	77.8	67.2	52.7	34.4	83.1	36.1
Nusa Tenggara Timur	65.5	61.4	60.0	59.4	63.0	62.5	60.1	57.0	43.2	29.0	58.3	38.0
Kalimantan Barat	59.2	51.8	43.7	34.7	37.2	38.3	25.7	22.0	17.3	9.6	32.4	21.2
Kalimantan Tengah	81.5	56.7	57.8	56.5	47.1	44.7	36.1	30.2	25.8	10.6	39.7	15.0
Kalimantan Selatan	49.2	61.0	43.1	43.6	42.7	34.0	31.6	24.6	16.7	5.7	29.8	11.5
Kalimantan Timur	32.1	35.3	32.7	28.2	21.8	17.8	18.3	14.6	8.6	6.4	19.0	15.9

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Sulawesi Utara	76.2	67.6	52.2	52.0	43.3	40.3	28.7	25.3	22.7	9.1	38.1	18.2
Sulawesi Tengah	72.2	60.2	67.1	49.7	40.2	43.4	45.6	25.6	16.5	6.2	46.2	32.6
Sulawesi Selatan	45.5	52.2	51.8	34.5	33.6	27.0	25.2	20.1	15.5	5.1	28.1	19.5
Sulawesi Tenggara	82.2	74.8	75.3	78.6	63.5	67.3	54.2	47.7	25.2	14.4	59.0	29.7
Gorontalo	55.7	47.4	44.5	52.3	56.0	36.4	32.4	22.2	13.5	5.8	39.9	37.7
Sulawesi Barat	80.2	79.1	59.8	58.2	47.4	46.3	42.5	51.0	16.8	16.8	51.7	30.3
Maluku	45.3	50.0	52.4	39.4	39.8	36.2	27.3	29.2	9.5	6.1	38.3	42.5
Maluku Utara	47.4	36.3	33.3	41.7	33.9	29.6	29.1	20.0	21.0	8.4	28.1	18.4
Papua Barat	54.1	58.6	57.1	52.7	43.8	35.9	34.6	29.1	14.8	3.4	45.5	48.2
Papua	23.0	37.9	39.5	33.8	27.8	43.3	32.8	34.9	23.9	16.5	29.3	44.1
gender												
male	74.9	68.2	62.5	54.2	50.6	44.7	36.3	26.9	19.0	8.0	46.6	28.7
female	75.4	68.6	63.7	55.7	50.5	44.9	36.4	27.0	18.6	7.7	46.6	28.4
hh head gender												
male	75.7	69.3	64.3	56.6	52.4	46.3	37.6	28.8	19.9	8.7	46.1	25.3
Female	82.3	79.3	75.7	69.9	63.6	60.8	53.9	44.3	32.9	14.6	56.9	22.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.17: BLT Coverage by Decile and Province, 2006

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	60.6	50.2	44.0	37.3	32.4	26.8	19.8	15.1	10.1	4.1	30.0	25.0
urban/rural												
urban	52.4	41.9	34.8	27.5	22.6	16.3	11.4	7.9	5.1	2.4	19.1	19.4
rural	65.3	54.9	49.8	44.2	39.7	35.4	28.0	23.2	17.6	8.3	39.9	30.1
region												
Sumatera	63.8	51.5	45.1	37.0	34.9	27.5	20.5	17.1	10.6	4.9	31.5	24.9
Jawa/Bali	56.9	47.4	41.5	34.8	29.1	24.2	17.6	12.3	8.8	3.1	27.5	24.8
Kalimantan	64.3	48.0	41.2	43.8	36.2	29.7	21.8	18.2	12.3	5.3	27.8	16.2
Sulawesi	62.8	55.5	48.6	42.3	36.6	28.9	23.4	19.5	12.3	5.2	32.7	24.3
NT	66.0	62.8	62.0	54.6	53.9	50.1	41.6	33.7	20.4	8.7	50.2	36.9
Maluku	55.6	57.6	47.3	42.8	34.4	44.6	22.7	20.9	8.9	6.0	36.5	32.5
Papua	93.9	85.9	77.2	70.8	71.6	55.1	48.0	39.9	30.5	21.8	68.1	45.1
province												
Aceh	77.0	68.3	61.8	56.1	48.3	43.8	38.3	35.9	22.8	10.0	53.4	37.4
Sumatra Utara	62.1	46.4	43.1	32.1	34.6	26.9	21.0	18.4	11.9	5.1	29.3	22.2
Sumatra Barat	63.8	45.9	40.5	32.8	32.5	28.6	19.9	12.1	5.5	1.5	25.1	18.9
Riau	51.0	53.3	51.5	25.2	22.5	13.7	9.9	12.5	5.1	2.9	20.1	17.0
Jambi	56.2	37.7	35.1	30.7	33.7	22.6	19.0	11.0	10.1	5.4	23.7	17.5
Sumatra Selatan	65.1	54.0	43.4	41.2	32.9	31.0	22.9	18.8	10.8	8.9	35.4	29.1
Bengkulu	61.0	50.4	47.2	44.6	39.4	24.1	18.9	17.4	8.1	6.2	35.2	32.0
Lampung	65.2	55.4	50.1	45.2	42.1	37.2	22.0	19.7	18.8	5.5	38.7	30.9
Bangka Belitung	25.4	20.2	12.5	9.3	13.0	11.1	3.6	6.9	1.9	1.3	9.5	18.5
Kepulauan Riau	46.3	30.9	22.5	14.8	27.9	11.7	19.1	9.1	1.9	0.0	16.7	17.1
DKI Jakarta	34.5	23.1	22.5	15.4	15.1	11.0	6.4	4.8	2.9	1.8	8.7	8.7
Jawa Barat	55.4	46.1	44.4	32.3	29.4	24.9	19.9	11.6	9.7	3.3	25.9	21.1
Jawa Tengah	58.8	53.6	44.5	39.4	34.5	27.5	20.8	15.9	10.2	3.2	34.4	31.3
DI Yogyakarta	59.5	43.1	43.2	35.4	27.4	23.5	17.7	10.2	9.7	3.3	28.1	29.1
Jawa Timur	56.6	44.9	38.5	34.8	24.7	22.9	15.7	13.1	8.8	3.7	28.7	29.5
Banten	66.1	47.4	43.9	41.2	36.3	29.6	20.1	13.2	9.6	2.2	25.0	13.7
Bali	39.4	38.1	22.7	25.8	30.2	18.7	11.6	13.1	5.1	3.1	16.2	12.8
Nusa Tenggara Barat	61.0	52.5	56.0	47.7	43.7	39.0	36.8	24.1	18.7	8.2	43.1	36.1
Nusa Tenggara Timur	73.2	75.6	69.2	64.4	68.7	64.4	47.8	46.6	23.0	9.5	59.8	38.0
Kalimantan Barat	60.8	51.3	47.0	46.2	38.3	30.6	23.8	17.7	17.3	4.8	32.0	21.2
Kalimantan Tengah	78.2	60.1	54.9	58.5	43.8	38.7	22.7	25.7	19.1	6.6	35.3	15.0
Kalimantan Selatan	67.1	43.1	32.5	36.9	35.6	29.1	21.0	17.7	9.0	4.3	23.2	11.5
Kalimantan Timur	60.1	36.2	28.2	36.5	28.9	22.4	19.6	13.2	5.6	6.1	22.0	15.9

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Sulawesi Utara	61.6	45.1	36.7	31.8	26.2	22.0	14.3	10.5	2.6	5.8	22.4	18.2
Sulawesi Tengah	57.4	57.1	43.0	29.5	25.9	21.0	17.9	15.6	8.3	5.4	31.6	32.6
Sulawesi Selatan	59.9	54.2	49.7	43.0	39.4	28.6	26.3	18.6	15.1	4.7	30.8	19.5
Sulawesi Tenggara	77.5	66.9	66.4	64.3	49.7	54.8	33.7	32.6	21.2	6.2	48.5	29.7
Gorontalo	56.3	44.4	47.4	36.9	38.2	26.6	24.5	24.3	3.6	2.9	34.8	37.7
Sulawesi Barat	71.8	60.8	54.9	54.1	38.4	32.7	18.8	35.0	13.2	7.5	40.8	30.3
Maluku	55.3	63.9	52.4	47.0	33.9	46.5	25.5	31.2	7.6	3.0	43.2	42.5
Maluku Utara	56.9	40.9	37.6	36.6	35.2	42.5	20.5	13.1	10.0	7.5	26.9	18.4
Papua Barat	95.2	75.8	70.4	47.3	45.5	22.0	33.2	17.7	22.1	6.7	59.9	48.2
Papua	93.4	90.3	80.3	79.8	80.1	67.3	55.9	47.3	32.7	23.7	71.0	44.1
gender												
male	59.4	47.8	41.4	34.4	28.4	23.1	16.7	12.0	8.1	3.6	29.2	28.7
female	60.8	48.8	41.9	35.3	29.9	23.8	17.5	12.6	8.2	3.3	29.8	28.4
hh head gender												
male	58.9	47.9	41.2	34.1	29.2	23.2	16.8	12.7	8.4	3.8	27.8	25.3
Female	73.7	65.3	61.8	57.8	52.9	47.8	38.0	29.9	20.9	5.7	44.5	22.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.18: Jamkesmas Coverage by Decile and Province, 2010

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	50.4	44.7	38.8	36.3	30.7	28.0	24.8	20.2	13.8	6.9	29.5	20.5
urban/rural												
urban	49.1	41.8	35.2	33.1	25.0	22.0	17.7	14.0	8.8	4.5	22.3	15.2
rural	51.2	46.4	41.4	38.8	35.3	33.3	31.5	26.9	21.7	13.9	36.3	25.6
region												
Sumatera	49.1	41.4	37.9	37.5	30.7	27.6	24.4	19.4	13.5	7.5	29.5	20.4
Jawa/Bali	48.5	43.9	36.9	33.7	28.5	25.8	22.5	17.2	10.8	5.1	27.2	19.9
Kalimantan	48.7	44.1	42.0	35.5	32.6	26.4	28.0	23.4	19.4	10.0	28.5	12.9
Sulawesi	55.2	46.6	40.3	40.8	37.6	36.6	32.5	31.9	22.7	10.4	33.6	21.6
NT	72.6	66.3	64.2	64.7	56.9	53.8	48.6	40.4	28.3	10.8	54.8	33.5
Maluku	50.9	36.6	48.7	33.4	34.6	42.0	29.1	37.0	25.0	10.2	35.8	27.2
Papua	41.1	45.8	55.6	58.2	46.0	43.7	44.4	39.4	36.0	30.0	42.9	43.0
province												
Aceh	79.9	70.8	74.2	69.4	69.8	51.2	51.2	41.3	29.0	10.5	62.0	28.9
Sumatra Utara	47.7	35.4	31.3	29.0	19.4	20.8	20.7	15.3	9.4	4.8	22.9	17.1
Sumatra Barat	56.4	47.8	38.4	41.4	38.3	27.1	20.8	16.7	14.1	5.0	28.9	15.6
Riau	35.9	34.9	30.4	35.9	21.8	27.0	13.9	13.2	10.0	3.7	21.3	14.4
Jambi	33.3	42.5	30.6	26.3	19.2	17.8	14.8	14.5	9.2	10.1	21.0	15.0
Sumatra Selatan	32.2	34.8	37.9	35.5	31.8	24.8	30.2	26.4	17.5	10.8	29.3	24.7
Bengkulu	53.6	41.3	39.2	38.0	21.5	33.7	32.6	23.1	14.1	10.0	32.9	29.3
Lampung	49.3	41.6	38.0	37.3	35.0	33.9	24.8	23.5	16.1	13.6	33.7	27.6
Bangka Belitung	31.5	34.4	22.0	28.8	31.4	19.4	23.5	10.3	9.1	8.5	21.1	11.6
Kepulauan Riau	59.9	23.8	45.8	34.7	34.6	30.5	35.6	25.2	17.4	12.5	31.0	11.7
DKI Jakarta	27.9	26.0	15.7	11.7	7.6	10.5	6.7	4.3	3.7	2.3	8.0	5.9
Jawa Barat	44.5	42.1	39.6	34.9	33.6	29.4	24.8	18.6	11.9	6.0	27.5	16.8
Jawa Tengah	56.3	50.2	43.5	39.1	32.1	29.8	28.7	22.1	13.8	5.1	34.7	25.5
DI Yogyakarta	58.0	50.9	40.5	31.6	29.3	28.5	24.5	15.6	9.2	2.9	28.7	24.5
Jawa Timur	43.2	38.5	30.8	31.9	25.4	21.3	18.9	13.8	7.3	5.6	25.6	24.5
Banten	61.0	62.8	43.1	38.4	26.3	32.8	25.5	24.3	15.9	4.8	27.5	10.7
Bali	40.3	27.1	28.0	22.3	21.3	18.3	15.6	13.0	11.2	7.1	16.9	9.9
Nusa Tenggara Barat	68.1	61.3	57.2	56.0	48.0	45.4	41.6	35.6	25.1	10.1	48.1	33.1
Nusa Tenggara Timur	78.3	72.6	73.0	74.2	66.1	63.2	57.2	49.1	33.6	12.1	63.3	34.0
Kalimantan Barat	46.3	49.9	47.0	43.4	41.6	31.8	40.3	29.9	29.6	8.3	35.7	16.9
Kalimantan Tengah	64.4	37.9	40.2	33.9	27.1	18.5	21.8	17.1	18.9	17.9	26.8	12.1
Kalimantan Selatan	45.6	45.0	40.6	25.8	30.5	27.3	22.2	22.0	17.3	8.1	24.9	10.4

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Kalimantan Timur	43.5	34.1	37.0	37.5	27.3	25.1	23.0	21.3	11.8	10.1	23.9	11.0
Sulawesi Utara	42.0	33.0	25.3	25.3	22.8	28.3	20.7	16.6	11.1	5.4	20.9	17.8
Sulawesi Tengah	52.9	46.6	42.2	28.7	32.5	33.6	22.3	27.0	15.4	8.6	32.0	26.0
Sulawesi Selatan	50.9	39.1	34.5	38.6	36.6	30.6	30.6	30.7	23.9	10.2	29.8	18.3
Sulawesi Tenggara	68.8	64.5	59.6	62.3	55.7	54.3	64.1	50.9	36.1	16.0	51.2	26.9
Gorontalo	67.9	66.6	54.1	54.7	55.5	61.9	38.2	51.9	33.4	8.2	49.8	32.7
Sulawesi Barat	49.3	57.8	64.3	68.9	46.2	53.8	36.0	32.5	25.9	21.7	45.3	21.5
Maluku	52.8	40.5	51.4	43.8	40.8	44.0	32.7	46.2	25.8	13.5	41.8	37.2
Maluku Utara	42.7	21.3	43.9	16.0	29.0	39.7	26.4	28.1	24.2	8.2	27.1	12.9
Papua Barat	75.0	58.7	65.4	75.4	55.0	47.0	52.0	46.3	28.6	22.0	58.0	39.9
Papua	30.2	41.5	51.6	50.5	38.9	42.3	41.1	37.4	38.0	32.2	37.4	44.1
gender												
male	50.4	43.9	38.0	35.3	29.0	26.1	22.6	18.2	12.6	6.6	29.8	24.3
female	51.2	44.5	38.4	35.1	28.9	27.1	23.9	18.6	12.7	6.2	30.2	24.5
hh head gender												
male	50.0	43.4	36.9	34.1	28.4	26.0	22.4	17.9	12.7	6.9	28.1	21.0
Female	53.4	53.7	49.3	49.5	43.1	39.1	36.9	31.7	19.6	6.4	37.2	17.9

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.19: Jamkesmas Usage by Decile and Province, 2010

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
national	15.3	13.5	11.6	11.2	9.9	8.6	8.3	6.4	3.4	2.6	9.1	22.2
urban/rural												
urban	18.4	15.3	11.4	11.6	9.2	7.4	7.3	5.0	2.5	1.9	7.7	16.2
rural	13.9	12.8	11.7	10.9	10.4	9.4	9.2	7.6	4.8	4.1	10.1	26.5
region												
Sumatera	15.4	13.4	10.1	11.4	9.5	8.5	6.9	6.3	3.6	3.8	8.9	21.5
Jawa/Bali	13.9	12.2	10.9	10.4	9.3	7.6	8.1	5.8	2.4	1.8	8.2	22.2
Kalimantan	23.1	13.7	13.6	11.0	9.3	8.0	8.7	5.9	5.5	3.2	8.8	13.5
Sulawesi	18.8	18.2	15.1	13.9	11.5	12.7	8.7	7.1	6.1	3.4	11.5	22.4
NT	18.9	21.7	18.0	14.2	18.2	17.5	16.1	15.1	8.9	9.1	16.6	32.7
Maluku	11.5	13.5	14.0	13.0	14.0	15.0	18.5	19.9	10.3	6.7	13.6	28.4
Papua	21.6	23.7	22.0	25.2	23.7	14.1	17.4	11.4	11.8	4.6	17.9	38.7
province												
Aceh	28.7	28.6	30.5	34.3	28.5	25.4	21.7	18.1	13.4	7.4	25.9	31.6
Sumatra Utara	12.6	8.9	6.4	6.7	5.9	5.9	4.7	5.9	1.9	5.3	6.2	17.8
Sumatra Barat	23.4	19.7	15.1	18.4	10.4	8.8	7.5	7.8	3.5	2.2	10.7	15.6
Riau	14.7	22.8	15.0	11.2	8.7	11.3	7.8	4.7	3.4	2.9	9.0	14.5
Jambi	7.0	17.2	10.3	8.8	3.4	5.6	4.7	1.9	1.8	1.2	5.7	14.2
Sumatra Selatan	9.6	7.0	6.8	6.4	10.2	7.1	6.5	5.1	3.1	3.4	6.7	25.1
Bengkulu	6.6	7.7	8.1	8.7	5.7	2.8	5.4	4.0	0.0	3.5	5.6	27.1
Lampung	16.5	11.0	5.4	8.4	9.5	8.1	6.2	8.0	5.5	3.7	9.0	31.8
Bangka Belitung	4.2	2.8	1.8	5.8	6.1	5.7	0.0	2.8	5.3	3.4	4.1	14.0
Kepulauan Riau	10.0	9.8	12.5	20.3	7.0	4.6	6.7	2.3	3.1	2.3	6.9	13.9
DKI Jakarta	8.7	2.7	0.7	3.0	0.8	0.6	1.7	1.0	0.4	0.3	1.2	7.0
Jawa Barat	15.8	11.4	10.9	11.3	11.5	8.5	9.3	6.3	3.2	2.5	8.7	19.0
Jawa Tengah	14.0	14.7	13.4	13.0	9.0	9.5	9.9	7.1	2.4	2.9	10.4	27.6
DI Yogyakarta	23.5	15.1	11.9	15.2	9.9	10.2	9.7	7.7	2.2	1.5	10.7	26.6
Jawa Timur	11.6	10.9	9.4	9.8	9.0	6.9	7.1	6.0	2.4	1.7	7.9	27.4
Banten	16.1	16.3	10.7	4.4	10.7	7.8	8.2	5.3	2.0	0.4	6.9	13.2
Bali	5.9	7.9	9.7	2.9	4.2	2.9	4.5	3.6	1.4	0.7	3.5	9.4
Nusa Tenggara Barat	17.7	20.3	16.6	10.1	14.5	14.4	15.0	11.1	11.0	8.4	14.7	32.5
Nusa Tenggara Timur	20.6	23.3	19.6	19.9	22.6	21.0	18.0	20.3	6.1	10.1	19.1	33.1
Kalimantan Barat	34.1	16.1	16.2	8.8	9.9	9.5	11.0	8.3	6.6	5.1	11.0	15.3
Kalimantan Tengah	11.8	10.1	10.1	10.8	8.5	7.5	6.7	3.3	5.4	0.8	7.0	15.3
Kalimantan Selatan	15.6	7.3	14.6	11.7	10.8	3.4	8.9	5.5	5.3	1.9	7.3	10.4
Kalimantan Timur	19.7	21.4	12.2	14.5	7.2	13.5	6.6	5.0	4.4	3.4	8.8	13.2

Level	Program Coverage by Household Consumption Decile (%)										Total coverage	Program target
	1	2	3	4	5	6	7	8	9	10		
Sulawesi Utara	15.4	13.8	11.0	11.8	8.5	7.7	3.3	2.3	0.8	1.9	7.3	16.8
Sulawesi Tengah	26.3	28.1	21.3	17.0	16.0	14.0	11.1	8.4	5.8	5.8	15.9	26.1
Sulawesi Selatan	16.1	13.1	13.2	10.6	9.9	11.8	8.2	8.5	6.6	3.1	9.7	19.8
Sulawesi Tenggara	14.4	20.7	12.5	19.3	9.3	24.5	11.3	4.3	7.9	2.6	13.1	27.5
Gorontalo	19.8	19.8	19.5	19.9	13.3	7.7	12.3	5.2	7.1	6.0	14.7	34.4
Sulawesi Barat	28.0	26.5	23.8	17.9	26.6	13.9	16.5	10.8	10.1	4.8	18.3	23.5
Maluku	13.6	15.9	14.4	9.8	13.0	9.8	17.6	16.0	4.1	6.4	12.6	37.1
Maluku Utara	3.0	6.1	13.0	19.0	15.9	20.5	19.4	21.1	15.0	6.9	15.0	15.8
Papua Barat	40.1	30.3	17.4	25.3	15.1	15.5	14.6	12.8	18.3	7.7	21.6	28.7
Papua	17.4	21.6	23.1	25.1	27.7	13.0	19.1	10.9	9.1	3.6	16.5	42.3
gender												
male	16.0	13.9	11.9	11.3	9.6	8.4	7.4	5.7	3.0	2.0	9.3	25.5
female	16.5	14.1	11.5	11.3	9.8	8.2	8.2	6.0	3.1	2.2	9.5	25.6
hh head gender												
male	14.9	13.0	11.4	10.7	9.3	8.0	7.4	5.5	3.0	2.2	8.6	22.6
Female	18.1	17.1	13.0	13.6	14.0	11.9	13.5	11.3	5.9	4.4	12.0	19.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

13.5 Indonesian Targeting Outcomes by Province, 2007-10: Program Benefit Incidence by Decile

Table 13.20: Raskin Benefit Incidence by Decile and Province, 2010

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	15.6	14.8	13.6	12.5	11.0	10.4	8.6	7.0	4.8	1.7
urban/rural										
urban	15.6	14.8	13.6	12.5	11.0	10.4	8.6	7.0	4.8	1.7
rural	15.6	14.8	13.6	12.5	11.0	10.4	8.6	7.0	4.8	1.7
region										
Sumatera	16.8	15.2	14.0	12.7	11.1	10.1	8.8	6.6	3.7	1.0
Jawa/Bali	14.6	14.5	14.0	12.9	11.3	10.6	8.8	6.9	4.7	1.6
Kalimantan	9.2	13.0	12.9	12.4	12.3	11.6	9.3	10.1	6.4	3.0
Sulawesi	18.2	15.8	11.1	9.2	9.3	9.0	6.8	8.8	8.2	3.4
NT	21.8	17.5	12.4	11.0	7.7	8.4	7.1	6.8	5.2	2.3
Maluku	22.4	13.2	9.7	8.2	9.8	11.4	9.6	7.5	6.0	2.2
Papua	32.7	15.5	9.4	7.9	6.9	6.6	7.8	5.5	4.1	3.6
province										
Aceh	20.7	16.9	11.9	14.1	12.0	10.6	5.8	4.8	2.4	0.8
Sumatra Utara	15.2	14.2	14.8	13.7	12.4	11.3	7.1	7.1	3.1	1.1
Sumatra Barat	14.0	15.2	13.1	13.8	11.9	10.1	11.4	6.5	3.4	0.5
Riau	10.6	12.9	15.8	15.1	10.6	11.0	9.4	9.8	3.3	1.5
Jambi	9.9	15.9	17.8	10.3	14.8	10.5	8.4	6.2	4.3	1.9
Sumatra Selatan	17.5	18.0	15.8	11.5	9.9	8.7	8.0	4.8	4.7	1.0
Bengkulu	24.3	17.6	12.6	11.1	6.8	8.5	8.3	5.0	3.7	2.1
Lampung	19.3	14.7	12.6	11.8	10.0	9.6	10.1	7.2	3.9	0.8
Bangka Belitung	0.0	10.2	28.6	23.4	14.3	0.0	4.1	10.2	9.2	0.0
Kepulauan Riau	11.8	8.5	13.6	10.8	12.1	11.6	16.9	7.4	6.5	0.9
DKI Jakarta	7.3	10.5	15.6	17.0	13.2	11.9	11.3	6.5	5.4	1.3
Jawa Barat	12.2	11.9	14.1	13.8	11.2	11.3	9.6	8.3	6.2	1.5
Jawa Tengah	15.8	15.7	13.4	12.6	11.3	9.9	8.7	6.5	4.3	1.8
DI Yogyakarta	24.7	18.5	13.9	11.2	7.8	8.3	6.6	5.9	2.4	0.7
Jawa Timur	16.7	16.6	14.8	12.3	11.6	10.5	7.5	5.5	3.1	1.3
Banten	8.4	11.7	11.8	13.6	11.6	13.3	12.3	8.8	6.7	2.0
Bali	8.0	10.9	12.9	10.3	11.6	10.6	9.5	9.9	11.1	5.0
Nusa Tenggara Barat	21.2	16.9	11.9	10.5	7.3	8.5	7.0	7.8	5.9	2.8
Nusa Tenggara Timur	22.8	18.6	13.2	11.9	8.3	8.2	7.3	4.6	3.8	1.2
Kalimantan Barat	9.3	14.1	11.2	12.0	11.6	12.4	9.6	10.9	5.4	3.5
Kalimantan Tengah	10.9	12.1	15.1	12.3	11.9	10.3	8.4	8.4	8.1	2.4

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Kalimantan Selatan	6.9	11.5	14.1	12.3	11.6	10.9	10.8	10.9	7.3	3.6
Kalimantan Timur	9.9	12.3	13.6	14.2	16.2	11.2	7.2	8.0	6.0	1.5
Sulawesi Utara	11.7	16.4	10.9	11.4	11.0	10.0	8.5	9.3	7.8	3.0
Sulawesi Tengah	25.7	18.4	12.0	9.3	8.7	7.3	5.9	6.4	4.7	1.5
Sulawesi Selatan	14.8	13.3	10.7	8.0	9.9	10.0	6.4	10.5	11.5	4.9
Sulawesi Tenggara	20.4	17.5	9.9	8.3	8.0	7.6	8.0	9.5	7.1	3.8
Gorontalo	29.0	17.8	9.0	8.6	8.0	7.9	4.0	6.3	8.4	1.0
Sulawesi Barat	13.2	14.9	16.6	13.1	9.5	10.8	7.5	6.8	4.7	2.9
Maluku	27.7	16.4	8.9	9.1	7.8	9.5	7.0	7.0	5.9	0.6
Maluku Utara	11.6	6.8	11.3	6.1	13.8	15.3	14.8	8.6	6.0	5.6
Papua Barat	34.9	10.9	9.6	10.7	9.1	6.4	6.7	5.9	4.0	1.6
Papua	31.6	17.8	9.2	6.5	5.8	6.7	8.4	5.3	4.1	4.7
gender										
male	15.3	14.8	13.7	12.6	11.2	9.9	8.9	6.9	4.8	1.8
female	15.5	14.9	13.7	12.5	11.3	9.9	8.9	6.8	4.9	1.7
hh head gender										
male	16.2	15.4	13.8	12.6	10.8	10.2	8.2	6.7	4.5	1.7
Female	12.5	11.9	12.8	12.1	12.0	11.0	10.8	8.8	6.3	1.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.21: Raskin Benefit Incidence by Decile and Province, 2009

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	15.6	14.7	13.7	12.5	11.4	9.9	8.7	6.9	4.5	2.1
urban/rural										
urban	16.5	14.4	13.5	12.7	11.1	10.2	8.8	6.8	4.3	1.7
rural	15.2	14.8	13.8	12.5	11.6	9.8	8.6	7.0	4.6	2.2
region										
Sumatera	16.2	15.3	14.1	14.1	11.3	9.2	8.3	6.5	3.4	1.5
Jawa/Bali	15.0	14.7	13.9	12.4	11.7	10.1	8.7	6.9	4.6	2.1
Kalimantan	10.1	11.1	11.3	11.6	11.1	11.4	11.7	10.5	7.7	3.4
Sulawesi	15.3	13.3	12.3	13.2	10.9	11.6	9.6	6.8	4.8	2.1
NT	20.7	16.6	13.5	12.0	10.0	7.6	7.2	5.9	3.8	2.7
Maluku	18.2	13.3	12.8	11.0	9.3	10.2	9.7	8.0	5.9	1.7
Papua	34.0	11.5	9.4	7.0	9.6	8.4	5.5	7.7	5.3	1.7
province										
Aceh	18.7	17.6	13.7	13.8	12.4	8.9	6.2	5.6	2.4	0.7
Sumatra Utara	14.6	15.6	13.2	14.1	11.4	10.1	9.9	7.1	2.2	1.9
Sumatra Barat	14.4	15.9	14.4	14.4	11.1	10.4	8.5	5.9	3.4	1.7
Riau	11.7	13.3	15.5	14.1	12.9	8.9	10.3	7.2	4.6	1.6
Jambi	7.7	11.7	14.9	16.5	11.2	9.6	10.4	10.8	6.0	1.2
Sumatra Selatan	18.9	14.3	14.6	13.4	9.4	9.1	7.4	7.8	4.2	1.0
Bengkulu	12.5	18.4	13.5	20.1	14.0	3.0	6.4	7.6	3.0	1.5
Lampung	20.1	15.7	14.5	13.5	10.5	8.7	6.7	5.1	3.5	1.7
Bangka Belitung	13.9	9.1	6.1	24.9	10.9	9.7	0.0	11.5	10.9	3.0
Kepulauan Riau	16.6	12.1	11.4	12.0	11.4	10.1	13.9	6.3	4.4	1.9
DKI Jakarta	7.6	12.6	13.0	16.8	15.2	10.8	7.3	9.2	6.7	1.0
Jawa Barat	12.9	13.2	12.8	12.0	11.5	11.3	9.7	8.7	5.6	2.1
Jawa Tengah	15.9	14.9	15.3	12.6	12.1	9.5	8.2	5.8	3.9	2.0
DI Yogyakarta	23.7	17.4	14.2	11.3	8.7	7.3	6.8	5.8	3.6	1.3
Jawa Timur	16.9	16.6	13.7	12.4	11.2	9.6	8.0	6.0	3.7	2.0
Banten	8.6	10.5	13.0	10.4	14.5	10.7	11.2	8.7	9.7	2.6
Bali	8.8	9.4	10.7	15.5	12.8	11.1	9.6	9.4	7.8	4.9
Nusa Tenggara Barat	19.9	15.6	13.3	11.9	10.0	7.5	8.1	6.5	4.4	2.8
Nusa Tenggara Timur	22.3	18.8	14.1	12.0	10.1	7.8	5.3	4.7	2.4	2.4
Kalimantan Barat	11.2	10.6	8.4	11.5	10.9	10.1	13.7	10.3	9.7	3.6
Kalimantan Tengah	7.7	15.7	15.7	12.2	7.8	11.2	9.9	11.7	6.5	1.6
Kalimantan Selatan	5.9	5.6	11.5	13.1	12.4	15.0	13.1	12.1	8.7	2.6
Kalimantan Timur	14.4	11.9	11.9	9.7	14.0	11.0	8.9	8.1	4.2	5.9

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Sulawesi Utara	10.6	11.6	14.7	15.0	11.1	11.1	11.4	7.0	4.8	2.6
Sulawesi Tengah	18.6	16.8	11.4	10.8	9.9	9.2	9.3	6.3	4.2	3.6
Sulawesi Selatan	14.7	12.1	10.6	12.2	10.6	15.5	9.9	8.1	4.9	1.4
Sulawesi Tenggara	16.4	13.7	15.4	16.0	12.2	6.8	6.7	4.4	6.3	2.2
Gorontalo	24.2	16.7	13.4	12.0	8.8	9.4	8.5	5.3	1.6	0.0
Sulawesi Barat	14.4	12.4	10.5	14.9	12.9	10.2	9.4	6.7	5.9	2.7
Maluku	24.8	16.7	15.0	12.2	9.6	8.0	6.5	3.3	3.5	0.5
Maluku Utara	3.6	5.7	8.0	8.1	8.5	15.2	16.8	18.6	11.2	4.4
Papua Barat	27.6	8.9	8.0	6.6	11.8	14.5	8.7	5.8	6.3	1.8
Papua	37.1	12.7	10.1	7.2	8.4	5.4	3.9	8.7	4.8	1.7
gender										
male	15.9	15.4	13.8	12.8	11.3	9.9	8.2	6.7	4.2	1.8
female	16.0	15.4	13.7	12.7	11.4	9.9	8.4	6.5	4.1	1.8
hh head gender										
male	16.0	15.2	14.2	12.6	11.3	9.5	8.3	6.6	4.3	1.9
Female	13.4	12.1	11.2	12.1	12.0	11.8	10.5	8.7	5.3	3.0

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.22: Raskin Benefit Incidence by Decile and Province, 2008

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	15.7	14.7	13.7	12.5	12.0	9.8	8.3	6.8	4.6	1.9
urban/rural										
urban	16.5	14.6	13.7	11.8	11.4	10.5	8.4	7.0	4.5	1.6
rural	15.4	14.8	13.7	12.8	12.3	9.5	8.3	6.6	4.6	2.1
region										
Sumatera	16.2	15.1	13.7	12.7	12.3	9.6	8.6	5.7	4.3	1.9
Jawa/Bali	15.5	14.8	13.8	12.6	12.1	9.9	8.2	6.9	4.4	1.8
Kalimantan	9.9	11.5	12.3	10.2	11.6	12.2	10.6	10.2	7.6	4.1
Sulawesi	15.4	12.5	14.2	12.8	12.2	9.4	9.5	6.9	5.0	2.1
NT	19.4	16.3	13.7	11.7	10.7	8.3	6.9	6.4	4.3	2.4
Maluku	23.6	11.4	12.5	9.1	7.4	10.9	9.5	7.0	6.3	2.3
Papua	28.6	16.6	13.1	9.0	7.1	6.1	6.2	4.9	6.2	2.1
province										
Aceh	20.4	15.6	17.0	12.0	10.2	9.0	6.4	4.9	2.9	1.6
Sumatra Utara	15.4	15.8	11.6	14.4	11.5	10.2	10.2	4.8	4.7	1.5
Sumatra Barat	8.7	14.3	16.2	12.3	17.5	10.7	10.1	5.6	3.4	1.2
Riau	11.3	12.5	15.0	12.7	13.7	10.0	12.1	7.0	4.9	0.8
Jambi	12.7	16.0	12.4	15.7	10.3	7.7	7.3	9.4	6.3	2.2
Sumatra Selatan	15.8	14.5	12.6	12.8	12.5	9.1	9.3	6.1	4.3	3.1
Bengkulu	22.4	14.9	13.7	16.1	9.9	8.1	6.5	4.8	2.2	1.5
Lampung	19.2	15.8	13.2	11.0	12.8	9.4	7.3	5.4	4.2	1.7
Bangka Belitung	11.6	17.0	14.0	15.0	13.3	8.4	9.5	6.7	2.4	2.1
Kepulauan Riau	5.9	10.9	15.0	9.4	12.4	15.1	10.4	7.9	9.1	3.9
DKI Jakarta	9.3	9.3	12.0	11.5	12.3	15.3	12.9	8.8	6.8	1.6
Jawa Barat	12.6	13.7	13.2	11.8	12.2	10.8	9.8	8.7	5.4	1.8
Jawa Tengah	16.7	15.2	14.4	13.5	11.9	9.5	7.2	5.9	3.7	1.9
DI Yogyakarta	22.9	18.0	15.2	12.5	10.3	6.9	6.1	4.3	3.1	0.6
Jawa Timur	17.6	15.7	13.9	12.4	11.9	9.1	7.5	6.1	4.2	1.6
Banten	8.9	14.1	13.1	15.2	17.2	12.2	7.7	6.0	3.8	1.8
Bali	6.9	13.2	10.8	12.0	12.5	13.6	11.8	10.4	5.6	3.1
Nusa Tenggara Barat	18.8	15.8	13.3	12.0	10.7	8.8	6.8	6.9	4.0	2.8
Nusa Tenggara Timur	21.2	17.7	15.0	10.7	10.6	6.5	7.2	4.5	5.5	1.2
Kalimantan Barat	10.2	13.0	12.0	10.2	11.8	12.0	8.2	9.7	7.4	5.5
Kalimantan Tengah	10.2	11.2	13.2	10.2	9.4	11.4	13.0	10.2	8.1	3.2
Kalimantan Selatan	6.9	10.1	11.5	11.0	13.9	11.3	11.9	12.1	8.3	3.0
Kalimantan Timur	14.2	9.4	13.2	8.2	10.5	15.4	12.0	8.5	5.7	2.7

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Sulawesi Utara	12.0	13.1	15.6	14.1	14.1	9.7	10.6	6.4	2.5	2.0
Sulawesi Tengah	20.9	14.5	15.0	14.9	9.6	8.6	5.5	5.3	3.7	1.9
Sulawesi Selatan	12.1	9.8	13.5	10.9	12.6	9.3	12.5	9.1	7.6	2.6
Sulawesi Tenggara	17.5	13.6	12.2	12.8	12.9	8.8	8.0	6.6	4.9	2.8
Gorontalo	23.3	17.3	15.6	11.7	11.5	8.2	6.8	2.8	2.3	0.6
Sulawesi Barat	13.1	12.9	14.3	14.4	13.4	13.7	8.4	5.4	2.8	1.6
Maluku	29.8	12.8	13.4	9.5	6.7	9.7	7.7	4.8	4.9	0.7
Maluku Utara	7.3	7.7	10.4	8.2	9.1	14.0	14.1	12.8	10.0	6.4
Papua Barat	26.4	18.2	14.7	8.0	5.9	9.6	7.6	4.6	4.9	0.0
Papua	29.7	15.8	12.3	9.6	7.7	4.4	5.4	5.0	6.9	3.2
gender										
male	15.6	14.8	13.7	12.4	11.7	10.2	8.3	6.8	4.6	1.9
female	15.8	14.8	13.9	12.3	11.8	10.2	8.2	6.5	4.6	2.0
hh head gender										
male	16.2	15.0	14.1	12.5	11.9	9.6	8.1	6.6	4.4	1.8
Female	13.4	13.2	12.0	12.3	12.4	11.0	9.8	7.9	5.4	2.8

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.23: Raskin Benefit Incidence by Decile and Province, 2007

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	16.1	14.9	13.8	12.3	11.3	10.2	8.4	6.5	4.6	2.0
urban/rural										
urban	17.4	15.1	14.5	12.4	11.4	9.9	8.3	5.8	3.8	1.5
rural	15.4	14.7	13.5	12.2	11.3	10.3	8.5	6.9	4.9	2.3
region										
Sumatera	16.7	15.7	13.7	12.1	10.9	10.5	8.2	6.2	4.0	1.9
Jawa/Bali	15.9	14.5	14.0	12.5	11.5	10.2	8.5	6.4	4.5	1.9
Kalimantan	9.0	13.2	10.7	11.8	13.3	11.7	10.5	9.1	7.5	3.4
Sulawesi	16.8	15.3	13.8	12.0	10.4	9.1	8.0	7.0	5.1	2.3
NT	18.2	16.5	14.0	10.6	10.6	8.9	7.6	6.1	4.6	2.9
Maluku	20.4	16.2	14.0	10.5	9.7	8.7	8.1	6.2	4.3	1.7
Papua	27.5	14.7	12.1	9.0	6.2	8.5	6.0	7.2	5.0	3.7
province										
Aceh	21.0	17.5	12.7	12.5	9.3	8.8	8.1	6.1	2.8	1.2
Sumatra Utara	14.8	16.4	13.9	12.0	11.5	11.5	8.5	6.3	3.8	1.1
Sumatra Barat	13.1	14.3	14.9	11.0	14.5	11.3	9.5	7.1	2.7	1.5
Riau	10.8	16.9	13.3	11.8	7.4	11.8	9.2	9.7	6.1	3.0
Jambi	11.1	12.1	11.1	11.6	12.5	15.6	11.5	6.3	4.8	3.4
Sumatra Selatan	18.6	14.8	14.2	13.6	10.3	9.3	7.6	4.9	4.3	2.4
Bengkulu	20.3	17.4	14.3	12.9	10.6	6.4	7.7	6.5	3.0	1.0
Lampung	18.5	15.6	13.2	12.0	11.3	10.1	7.1	5.7	4.2	2.1
Bangka Belitung	8.5	11.3	18.6	9.8	15.6	14.6	10.5	7.4	2.3	1.4
Kepulauan Riau	10.1	11.7	18.2	8.1	12.7	13.7	9.4	7.3	6.7	2.0
DKI Jakarta	7.3	8.9	12.8	11.0	14.6	12.8	12.0	12.0	6.5	2.1
Jawa Barat	12.8	14.1	13.2	12.5	11.3	11.0	9.9	7.2	5.7	2.3
Jawa Tengah	16.5	15.8	15.2	12.5	12.0	9.6	7.2	5.8	3.8	1.6
DI Yogyakarta	21.7	15.8	16.7	11.5	10.3	7.9	5.8	4.6	4.7	1.0
Jawa Timur	19.6	14.5	13.8	12.8	10.8	9.9	7.8	5.7	3.4	1.6
Banten	9.7	10.1	11.9	12.7	14.8	11.6	12.0	8.4	6.8	1.8
Bali	6.0	10.6	11.2	11.8	13.1	13.6	12.2	11.0	6.7	3.7
Nusa Tenggara Barat	18.8	16.7	14.0	11.0	10.8	8.4	7.2	5.7	4.5	2.8
Nusa Tenggara Timur	16.9	16.2	14.1	9.7	10.2	9.9	8.3	6.9	4.8	3.1
Kalimantan Barat	12.0	16.7	11.1	10.1	11.8	12.5	8.8	7.7	6.2	3.0
Kalimantan Tengah	8.9	10.2	11.4	12.8	13.2	11.5	10.0	9.8	8.7	3.5
Kalimantan Selatan	4.8	11.8	9.6	12.7	14.9	12.0	12.4	10.1	8.9	2.9
Kalimantan Timur	9.8	12.6	10.6	12.3	13.8	9.8	11.6	9.0	5.8	4.8

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Sulawesi Utara	12.7	12.3	13.8	12.2	10.7	11.9	8.0	8.3	7.2	2.8
Sulawesi Tengah	22.2	16.2	17.1	10.2	8.5	8.4	8.4	4.8	3.1	1.0
Sulawesi Selatan	13.7	14.6	13.3	12.4	11.5	9.0	8.8	7.2	6.8	2.7
Sulawesi Tenggara	18.9	15.0	12.1	12.2	10.9	8.2	7.7	8.4	4.0	2.5
Gorontalo	23.7	16.9	13.5	14.7	9.2	8.8	5.5	4.3	2.2	1.2
Sulawesi Barat	15.4	21.6	12.9	12.1	9.2	8.3	6.7	7.7	3.5	2.6
Maluku	25.6	19.2	16.0	9.3	9.6	7.5	5.3	5.0	1.8	0.7
Maluku Utara	10.4	10.2	10.2	13.0	9.9	11.1	13.5	8.7	9.3	3.6
Papua Barat	35.7	16.7	13.7	9.6	5.9	5.7	6.1	4.5	2.0	0.2
Papua	23.1	13.6	11.2	8.7	6.3	10.1	6.0	8.7	6.6	5.6
gender										
male	16.3	14.9	14.2	12.2	11.2	10.1	8.5	6.4	4.4	1.8
female	16.3	14.9	14.1	12.3	11.2	10.1	8.6	6.3	4.4	1.8
hh head gender										
male	16.8	15.1	14.0	12.3	11.4	9.9	8.1	6.2	4.3	1.9
Female	12.4	13.4	13.1	12.1	11.2	11.5	9.9	7.9	5.9	2.7

Source: Susenas and World Bank Calculations

Notes:

1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.24: BLT Benefit Incidence by Decile and Province, 2006

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	20.2	16.7	14.6	12.4	10.8	8.9	6.6	5.0	3.4	1.4
urban/rural										
urban	20.9	16.9	14.9	12.5	10.6	8.1	6.2	4.6	3.4	1.9
rural	19.9	16.6	14.5	12.4	10.9	9.3	6.8	5.2	3.4	1.1
region										
Sumatera	19.6	16.8	14.0	11.9	11.2	9.3	6.8	5.8	3.3	1.3
Jawa/Bali	20.3	16.9	15.5	12.8	10.6	8.8	6.4	4.4	3.2	1.2
Kalimantan	11.5	13.3	10.7	14.0	14.1	11.1	9.0	7.8	5.9	2.5
Sulawesi	19.7	16.4	13.6	12.7	10.7	8.3	6.7	6.0	4.2	1.9
NT	20.5	18.4	15.8	10.6	10.6	8.9	6.5	4.7	2.8	1.1
Maluku	23.3	18.8	13.5	10.4	8.3	11.0	6.1	5.1	2.3	1.3
Papua	40.7	14.1	10.2	8.0	6.8	5.6	4.2	4.2	3.4	2.6
province										
Aceh	23.8	18.7	12.9	12.6	9.3	7.7	6.6	5.3	2.5	0.6
Sumatra Utara	15.0	16.4	13.9	11.6	11.7	10.3	8.1	7.4	4.1	1.4
Sumatra Barat	16.2	14.9	13.8	11.0	13.1	12.7	8.7	6.3	2.8	0.6
Riau	15.6	20.1	16.9	10.8	9.8	7.5	5.6	8.2	3.6	1.8
Jambi	13.3	11.7	13.4	10.9	15.8	12.3	9.9	5.4	5.2	2.1
Sumatra Selatan	22.6	16.7	13.7	13.0	10.0	9.0	6.3	4.5	2.2	2.0
Bengkulu	23.1	17.4	16.2	14.9	9.9	5.9	5.0	4.5	1.9	1.2
Lampung	23.2	17.0	13.9	11.8	11.2	8.8	4.7	4.3	3.9	1.3
Bangka Belitung	15.6	16.1	11.9	9.1	15.1	14.8	5.2	9.1	2.2	1.0
Kepulauan Riau	16.7	11.6	13.4	8.1	18.2	9.8	14.7	6.4	1.1	0.0
DKI Jakarta	8.1	10.1	14.5	11.3	16.1	12.5	9.7	8.5	5.2	4.0
Jawa Barat	16.4	16.5	16.0	12.2	10.5	9.7	8.1	4.9	4.3	1.5
Jawa Tengah	21.1	19.1	16.1	13.1	11.1	7.9	5.1	3.7	2.1	0.6
DI Yogyakarta	26.7	16.2	17.3	11.0	8.6	7.3	5.0	2.7	3.7	1.5
Jawa Timur	25.8	16.7	15.0	13.2	8.9	7.9	5.2	3.9	2.5	1.0
Banten	11.2	11.8	12.8	14.0	15.0	12.0	10.4	6.4	5.2	1.3
Bali	8.2	13.0	10.3	12.3	15.7	13.3	8.3	11.1	4.7	3.0
Nusa Tenggara Barat	22.7	17.4	15.8	11.0	10.3	7.9	6.6	3.9	3.1	1.3
Nusa Tenggara Timur	18.4	19.4	15.8	10.3	10.9	9.9	6.4	5.5	2.5	1.0
Kalimantan Barat	12.5	16.8	12.2	13.7	12.3	10.1	8.2	6.3	6.3	1.5
Kalimantan Tengah	9.6	12.2	12.1	14.9	13.7	11.2	7.1	9.4	7.2	2.5
Kalimantan Selatan	8.4	10.7	9.3	13.7	15.9	13.2	10.6	9.3	6.1	2.9
Kalimantan Timur	15.9	11.2	7.9	13.8	15.8	10.6	10.7	7.0	3.2	3.9

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Sulawesi Utara	17.4	14.0	16.6	12.7	11.0	11.1	6.8	5.9	1.4	3.1
Sulawesi Tengah	25.9	22.5	16.0	8.9	8.0	6.0	4.8	4.3	2.3	1.2
Sulawesi Selatan	16.4	13.8	11.7	14.2	12.3	8.7	8.4	6.1	6.1	2.3
Sulawesi Tenggara	21.7	16.4	13.0	12.1	10.4	8.1	5.8	7.0	4.1	1.3
Gorontalo	27.4	18.2	16.4	11.9	7.2	7.4	4.7	5.4	0.7	0.7
Sulawesi Barat	17.5	21.0	15.1	14.2	9.4	7.4	3.7	6.7	3.5	1.5
Maluku	27.7	21.8	14.2	9.8	7.3	8.5	4.4	4.7	1.3	0.3
Maluku Utara	13.1	11.9	12.0	11.9	10.7	16.5	9.9	6.0	4.6	3.4
Papua Barat	47.8	16.4	12.8	6.5	4.7	2.6	4.5	2.1	2.2	0.4
Papua	38.7	13.4	9.4	8.5	7.5	6.5	4.2	4.9	3.7	3.3
gender										
male	21.0	16.9	14.9	12.7	10.4	8.9	6.4	4.5	3.0	1.3
female	20.9	16.9	14.7	12.6	10.5	8.9	6.6	4.7	3.1	1.2
hh head gender										
male	21.7	17.4	14.9	12.3	10.5	8.3	6.0	4.6	3.0	1.4
Female	14.2	14.1	13.6	12.8	11.9	11.5	8.9	6.9	4.8	1.3

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

Table 13.25: Jamkesmas Coverage Benefit Incidence by Decile and Province, 2010

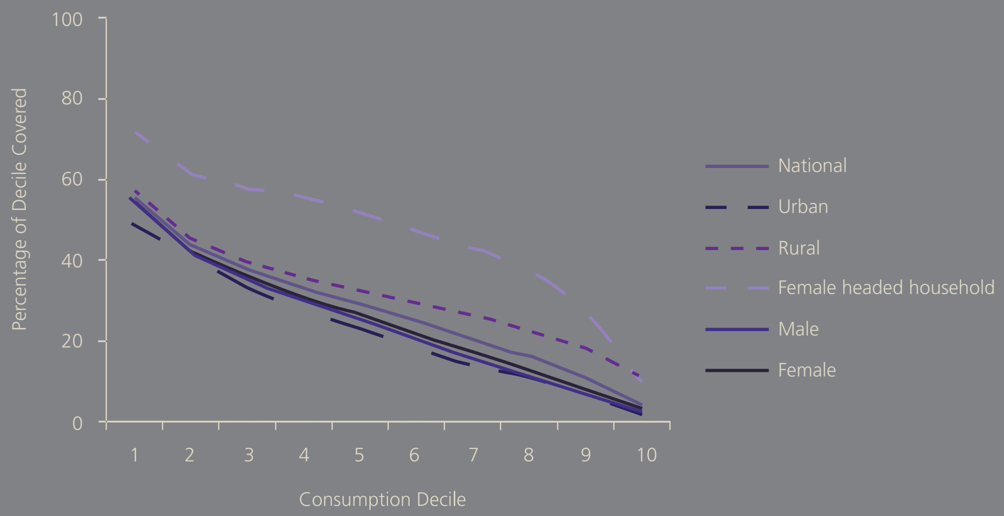
Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
national	17.1	15.2	13.2	12.3	10.4	9.5	8.4	6.9	4.7	2.3
urban/rural										
urban	16.3	13.9	13.7	13.4	10.4	9.5	7.9	6.7	4.9	3.1
rural	17.6	15.9	12.8	11.7	10.4	9.5	8.7	6.9	4.6	1.9
region										
Sumatera	16.4	14.1	13.3	13.2	11.2	10.0	8.9	7.0	4.2	1.9
Jawa/Bali	16.9	15.9	13.9	12.7	10.6	9.6	8.4	6.1	3.9	1.9
Kalimantan	8.6	11.6	12.7	11.7	11.9	9.7	10.3	10.6	8.1	4.7
Sulawesi	17.5	14.5	10.1	9.5	9.0	8.5	7.7	9.8	8.6	4.9
NT	24.0	17.6	12.0	11.9	8.2	8.5	6.6	5.7	4.1	1.5
Maluku	21.3	12.1	10.7	7.8	9.0	11.8	8.1	10.2	6.6	2.4
Papua	30.2	11.8	8.5	8.6	6.0	6.5	8.2	7.2	7.5	5.5
province										
Aceh	20.0	14.8	12.7	15.1	14.0	9.2	6.6	4.3	2.8	0.6
Sumatra Utara	16.5	13.3	13.6	13.4	9.8	10.5	9.9	7.6	3.7	1.8
Sumatra Barat	14.1	12.8	12.9	14.7	13.2	10.1	8.7	6.5	5.3	1.7
Riau	9.8	13.3	13.7	16.9	10.0	13.7	7.5	8.4	4.9	1.8
Jambi	9.1	17.9	16.5	11.7	11.1	8.9	7.4	8.9	5.4	3.0
Sumatra Selatan	13.1	14.8	14.6	11.6	11.5	7.7	9.9	8.7	5.8	2.2
Bengkulu	23.6	18.2	11.8	10.0	5.2	10.0	8.5	6.4	3.5	2.7
Lampung	21.4	15.2	12.7	11.8	9.4	9.8	7.7	6.4	3.4	2.2
Bangka Belitung	6.3	11.1	9.9	13.4	19.2	11.6	14.6	5.8	4.9	3.1
Kepulauan Riau	11.4	4.0	10.9	9.9	14.9	11.8	17.5	9.6	6.2	3.7
DKI Jakarta	8.2	10.8	13.8	13.8	9.1	15.1	10.8	6.9	6.5	5.2
Jawa Barat	13.2	12.5	14.6	12.9	11.7	10.8	9.5	7.2	5.1	2.4
Jawa Tengah	19.8	18.2	14.0	12.2	9.9	8.5	7.9	5.3	3.2	1.0
DI Yogyakarta	26.1	19.5	13.3	9.4	8.1	7.5	6.7	4.6	2.9	1.7
Jawa Timur	19.7	18.2	13.7	13.1	11.0	8.8	7.1	4.7	2.2	1.4
Banten	10.5	13.3	11.9	13.3	9.1	11.7	10.4	9.6	6.9	3.3
Bali	8.3	9.6	13.2	11.9	11.6	9.6	9.2	8.5	10.0	8.2
Nusa Tenggara Barat	25.1	18.2	12.0	10.9	7.1	7.6	6.2	6.6	4.5	1.8
Nusa Tenggara Timur	22.9	17.0	11.9	12.9	9.3	9.3	6.9	4.9	3.7	1.2
Kalimantan Barat	8.2	14.2	12.1	12.0	12.0	8.6	11.7	10.4	8.0	2.8
Kalimantan Tengah	12.0	9.8	14.1	12.7	11.2	7.7	8.3	8.3	9.0	6.9
Kalimantan Selatan	6.6	11.6	14.1	9.8	11.7	10.9	9.4	12.1	8.8	5.1
Kalimantan Timur	9.1	7.8	11.0	12.7	12.7	12.5	10.2	11.4	6.7	6.1

Level	Benefit Incidence by Household Consumption Decile (%)									
	1	2	3	4	5	6	7	8	9	10
Sulawesi Utara	13.3	16.6	12.9	10.2	9.0	10.4	8.4	8.0	6.9	4.3
Sulawesi Tengah	23.5	16.5	12.6	7.4	8.4	8.8	5.5	9.4	5.1	2.8
Sulawesi Selatan	15.0	12.0	8.6	9.7	10.1	8.0	8.4	10.6	11.4	6.3
Sulawesi Tenggara	18.8	15.7	9.0	9.3	7.5	7.3	9.3	10.7	7.5	4.9
Gorontalo	26.1	17.8	8.3	8.2	8.5	7.6	4.6	9.1	7.8	2.1
Sulawesi Barat	10.6	14.3	15.1	14.0	8.5	11.7	7.0	6.8	6.6	5.4
Maluku	26.1	15.6	10.5	9.3	7.3	9.5	5.6	9.1	5.2	1.7
Maluku Utara	10.5	4.6	11.3	4.5	12.8	17.0	13.4	12.5	9.7	3.9
Papua Barat	37.4	10.6	8.2	9.6	8.9	5.8	8.2	5.3	3.6	2.4
Papua	26.2	12.4	8.6	8.0	4.4	6.9	8.3	8.3	9.7	7.2
gender										
male	16.9	15.1	13.5	12.3	11.0	9.3	7.9	6.9	4.6	2.4
female	17.2	15.2	13.5	12.0	10.8	9.1	8.2	7.0	4.7	2.3
hh head gender										
male	16.9	15.1	13.5	12.3	11.0	9.3	7.9	6.9	4.6	2.4
Female	17.2	15.2	13.5	12.0	10.8	9.1	8.2	7.0	4.7	2.3

Source: Susenas and World Bank Calculations
Notes:
1. The program is targeted at poor and near poor households. The program target presented is the near poor rate.
2. All numbers are calculated using household weights except for the gender category which uses individual weights.
3. Deciles are the national household deciles using real per capita expenditures.

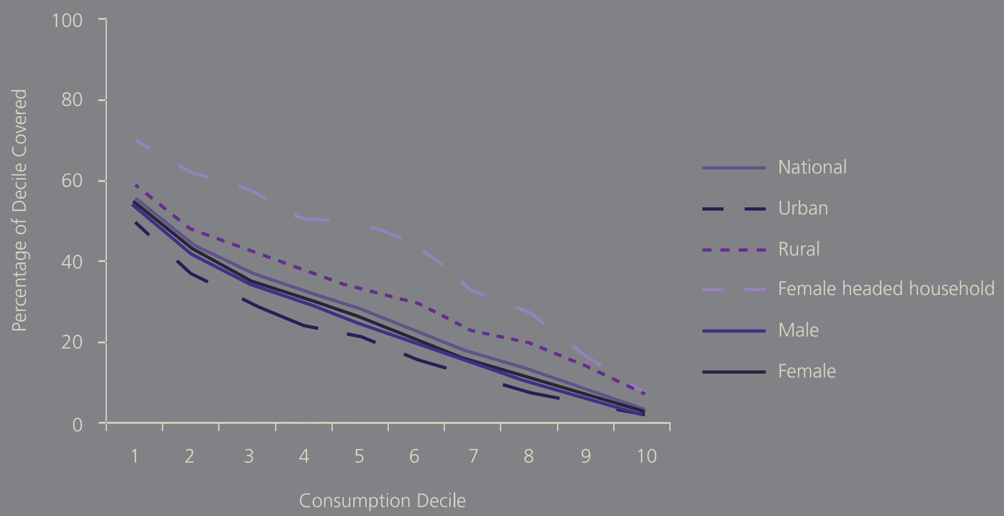
13.6 Indonesian Targeting Outcomes by Program by Beneficiary Type

Figure 13.1: BLT 2005-06 Coverage by Per Capita Consumption Decile



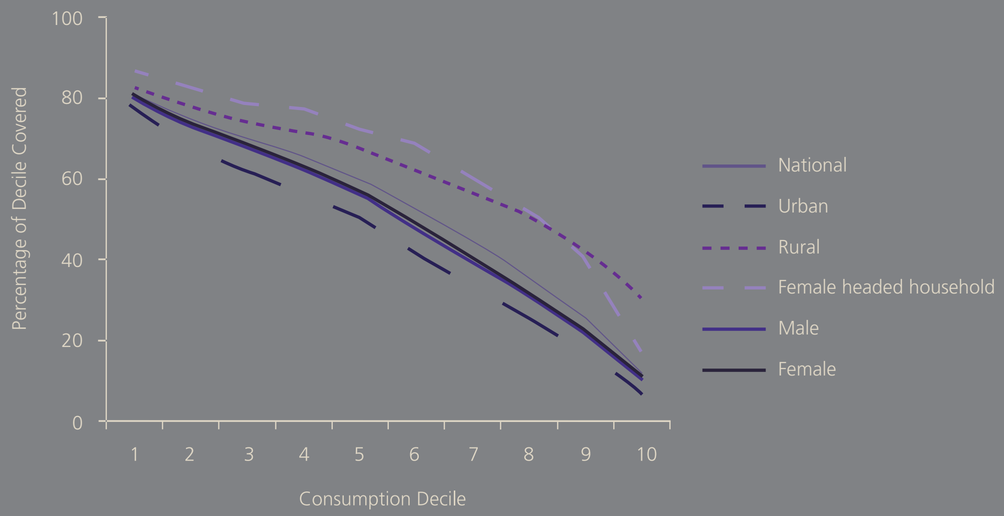
Source: Susenas

Figure 13.2: BLT 2008-09 Coverage by Per Capita Consumption Decile



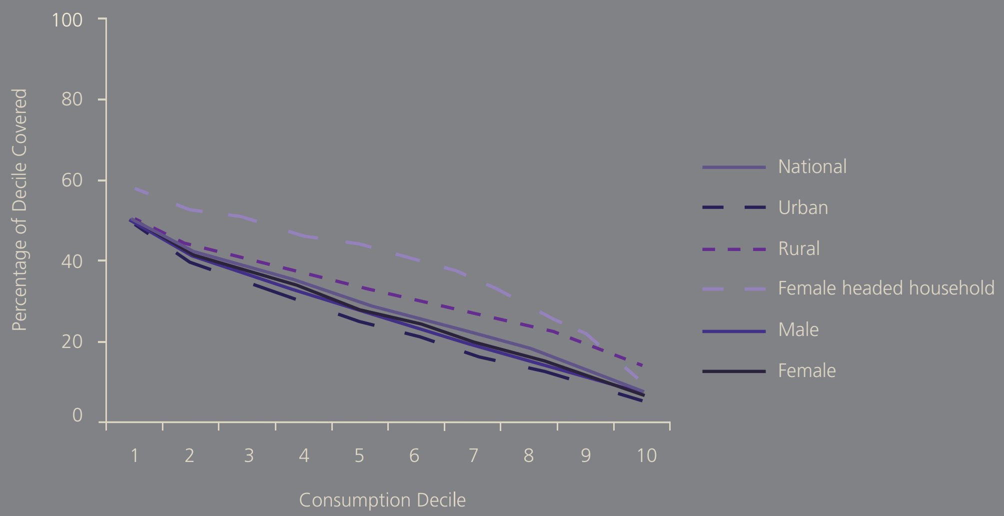
Source: Susenas

Figure 13.3: Raskin 2009 Coverage by Per Capita Consumption Decile



Source: Susenas

Figure 13.4: Jamkesmas 2009 Coverage by Per Capita Consumption Decile



Source: Susenas

13.7 International Targeting Outcomes by Program Type

Table 13.26: International Comparisons: Program Coverage of Households by Consumption Decile (%)

Country	Year	Total	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
*Cash Transfers**												
Brazil	2006	21	51	53	41	28	20	12	6	3	1	0
Mexico	2008	20	56	41	31	23	17	13	8	5	2	1
Ecuador	2008	34	55	60	52	49	39	30	24	15	9	2
Hungary	2004	15	59	33	18	12	8	6	4	3	2	1
Sri Lanka	2008	29	55	47	43	37	32	26	21	15	10	3
Uruguay	2008	30	65	59	48	39	31	23	17	11	5	2
Indonesia	2009	31	62	51	44	38	32	27	22	16	10	5
In-kind Food Assistance												
Chile	2006	31	51	49	42	38	33	29	26	21	14	6
Turkey	2008	34	52	42	36	41	32	28	33	27	26	18
India	2005	24	36	35	33	31	28	25	20	17	11	5
Peru	2008	31	65	55	47	37	32	27	20	14	11	4
Uruguay	2008	8	28	22	13	8	5	2	1	0	0	0
Indonesia	2009	50	80	74	69	64	58	50	42	34	23	10
Social Security / Health Insurance												
Vietnam	2006	12	42	27	18	9	7	5	5	3	1	1
Indonesia	2009	33	56	48	44	40	36	31	27	23	17	10

Source: Social Protection Atlas (World Bank), from Social Protection module of ADePT.
Notes: Cash transfer programs vary in type. Brazil and Mexico are conditional cash transfer programs, Ecuador, Hungary, Sri Lanka and Indonesia are unconditional cash transfers or last resort programs, Uruguay is an 'other cash transfer" program, such as family, child or disability allowance. ADePT groups social security and health insurance programs together.

Table 13.27: International Comparisons: Program Distribution of Beneficiaries by Consumption Decile (%)

Country	Year	Total	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
*Cash Transfers**												
Brazil	2006	100	24	25	19	13	9	6	3	1	0	0
Mexico	2008	100	28	21	16	12	9	7	4	2	1	0
Ecuador	2008	100	16	18	15	15	12	9	7	5	3	1
Hungary	2004	100	41	22	12	8	5	4	3	2	1	1
Sri Lanka	2008	100	19	16	15	13	11	9	7	5	3	1
Uruguay	2008	100	22	20	16	13	10	8	6	4	2	1
Indonesia	2009	100	20	17	14	12	11	9	7	5	3	1
In-kind Food Assistance												
Chile	2006	100	17	16	14	12	11	9	9	7	4	2
Turkey	2008	100	16	13	11	12	10	8	10	8	8	5
India	2005	100	15	14	14	13	12	10	8	7	5	2
Peru	2008	100	21	18	15	12	10	9	6	4	3	1
Uruguay	2008	100	35	27	17	10	7	3	2	1	0	0
Indonesia	2009	100	16	15	14	13	12	10	8	7	5	2
Social Security / Health Insurance												
Vietnam	2006	100	36	23	15	8	6	4	4	2	1	1
Indonesia	2009	100	17	15	13	12	11	10	8	7	5	3

Source: Social Protection Atlas (World Bank), from Social Protection module of ADePT.
Notes: Cash transfer programs vary in type. Brazil and Mexico are conditional cash transfer programs, Ecuador, Hungary, Sri Lanka and Indonesia are unconditional cash transfers or last resort programs, Uruguay is an 'other cash transfer" program, such as family, child or disability allowance. ADePT groups social security and health insurance programs together.

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