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Inequality, Elite Capture, and Targeting of Social Protection Programs:

Evidence from Indonesia

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ABSTRACT

Inequality, Elite Capture, and Targeting of Social Protection Programs: Evidence from Indonesia

Armand Sim, Radi Negara, and Asep Suryahadi

This paper investigates the relationships between inequality, elite capture, and targeting performance of the two biggest social protection programs in Indonesia, the Rice for the Poor (Raskin) and Direct Cash Transfer (BLT) programs. Both programs differ in their targeting methods. While targeting in Raskin is decentralized, targeting in BLT is more centralized. Using data from 2009 National Socioeconomic Household Survey (Susenas) and 2008 Village Census (Podes), we find that an increase in Gini ratio is not significantly associated with a change in inclusion error in both programs, indicating the existence of elite capture in both programs. However, an increase of 0.01 point in Gini ratio is associated with a reduction of 0.55 percentage point in exclusion error of BLT, while the elasticity is smaller in Raskin with only 0.50, implying a larger elite capture in this program.

Keywords: inequality, targeting, social protection, elite capture, Indonesia

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BLT	:	*Bantuan Langsung Tunai*	Direct Cash Transfer
Bulog	:	*Badan Urusan Logistik*	National Logistics Agency
IDT	:	*Inpres Desa Tertinggal*	Presidential Instruction on Disadvantaged Villages
JPS	:	*Jaring Pengaman Sosial*	Social Safety Net
OPK	:	*operasi pasar khusus*	special market operation
PKPS-BBM	:	*Program Kompensasi Pengurangan Subsidi BBM*	Fuel Subsidy Reduction Compensation Program
Podes	:	*Pendataan Potensi Desa*	Village Potential Survey
PSE-05	:	*Pendataan Sosial-Ekonomi Penduduk 2005*	2005 Socioeconomic Data of the Population
Raskin	:	*Beras untuk Keluarga Miskin*	Rice for Poor Households
SLS	:	*satuan lokal setempat*	local area unit
Susenas	:	*Survei Sosial-Ekonomi Nasional*	National Socioeconomic Survey

I. INTRODUCTION

Social protection programs are vital in preventing vulnerable individuals and households from falling below the poverty threshold when an adverse shock occurs. However, their effectiveness is compromised when the government does not have the capability to identify target households correctly. Incorrect identification of beneficiaries is costly as the money spent on social protection programs then becomes wasted. On the other hand, when targeted correctly, social protection programs are effective in increasing consumption among the poor and hence in reducing poverty incidence (Sumarto and Suryahadi, 2010).

During the Asian financial crisis, to minimize the severity of economic hardship among the poor and near-poor, the Indonesian government launched the first massive social safety net (JPS) programs, which covered community empowerment, education, health, and employment creation programs.[1] The government allocated almost one third of the total development budget in 1998, which was worth Rp14 trillion (around USD 1.4 billion), to the JPS programs.

Another major initiative was introduced in 2005. In response to a large fuel subsidy reduction caused by a sharp increase in world oil prices, the government made a steep 150% increase in the gasoline price and an even steeper 185% increase in the price of kerosene (Alatas, Purnamasari, and Wai-Poi, 2011). In exchange, a compensation fund worth Rp11 trillion was prepared to launch several social protection programs, ranging from education, health and direct cash transfers, to rural infrastructure programs. These programs are known as the fuel subsidy reduction compensation (PKPS-BBM) programs.

Unfortunately, a large proportion of the benefits were wasted due to misdirection. In general, the targeting performance of both the JPS and PKPS-BBM programs was poor. Sumarto, Suryahadi, and Widyanti (2010) find that all JPS programs suffered from both type I (exclusion) and type II (inclusion) errors.

This motivates us to investigate the factors that affect the targeting performance of social protection programs in Indonesia. In particular, we investigate how inequality and elite capture affect targeting performance. Coady, Grosh, and Hoddinott (2004) show that targeting performance in more unequal countries is generally better than in countries with lower inequality levels.

Inequality affects targeting performance as, to some extent, it affects the performance of beneficiary identification. This has been confirmed in the case of Indonesia in a pre-Asian financial crisis program by Yamauchi (2010). She suggested that high inequality within villages significantly contributes to ease the identification of beneficiaries resulting in decent targeting performance.

Meanwhile, conditional on the level of government, elite capture is also critical in affecting targeting performance. This is especially true at the lowest government level as the lower the level of government, the greater the extent and possibility of elite capture (Bardhan and Mookherjee, 2000). Bardhan and Mookerjee suggested that greater elite capture implies less protection for minorities and the poor, which implies worse targeting performance in the context of social protection programs. Indeed, Mulyadi (2013) found that elite capture has been instrumental in affecting targeting performance of various government programs in Indonesia.

[1]For detailed coverage on JPS, see Pritchett, Sumarto, and Suryahadi (2002).

In our analysis, we focus on the Rice for the Poor (Raskin) and Direct Cash Transfer (BLT) programs as they are arguably the two biggest government social protection programs in Indonesia in terms of budget and number of beneficiaries. Interestingly, the government employs different targeting methods for each program. Targeting is decentralized in Raskin, but more centralized in BLT. Previous studies show more virtues of decentralized over centralized targeting methods (i.e., Alderman, 2002).

Our results resonate with the results of the majority of the studies cited in Coady, Grosh, and Hoddinott (2004). We find that exclusion error in targeting BLT recipients decreases in communities with higher inequality levels. This result is also found in relation to Raskin. However, the effect of inequality on reducing exclusion error is higher in BLT than in Raskin. We find that the inequality elasticity of exclusion error in BLT is 0.55, while only 0.50 in Raskin. On the other hand, inequality has no impact on inclusion error in both BLT and in Raskin.

We interpret the results as indirect evidence of the existence of elite capture. In addition, we also find heterogeneous impacts by level of inequality, educational attainment, and urban/rural location. Using an alternative measure of inequality, the Palma ratio, we find our regression results are similar to the results when we use the Gini ratio, which indicates robustness of our specifications.

However, our results are only partially similar to those of a study by Yamauchi (2010). Evaluating the Presidential Instruction on Disadvantaged Villages (IDT), an antipoverty program in Indonesia in the 1990s, she found a positive relationship between inequality and targeting performance, but she suggested that elite capture did not exist. Yamauchi (2010) concluded that her findings suggest that IDT was free from elite capture as village heads did not want to deviate from the national orders to target the poor. Perhaps this conclusion is justifiable since at that time the government was heavily centralized.[2] The Indonesian context is now different because a major governmental decentralization took place in 2001 that gave way for local elites to pursue their own interests.

The rest of this paper is structured as follows. Section II discusses the issues of targeting in social programs in the context of both developing countries in general and Indonesia specifically. Section III provides a brief description of the Raskin and BLT programs, including their targeting methods. Section IV discusses our conceptual framework. Section V describes the data, descriptive statistics, and identification of program beneficiaries. Section VI discusses the empirical strategy and estimation results. Section VII provides the results of heterogeneity analysis and robustness check. Section 8 concludes.

[2]President Soeharto was a dictator in Indonesia for more than three decades from 1966 to 1998. During his reign, Indonesia was heavily centralized. Major decisions aimed at regional level came directly from the central government.

II. TARGETING ISSUES IN SOCIAL PROTECTION PROGRAMS

2.1 Targeting in Developing Countries

Decentralizing authority to local government is often considered as the most efficient and effective way to attain the best targeting performance in social protection programs. The main argument is that local governments know local societies better than the central government, suggesting better identification of targeting beneficiaries.

Alderman (2002) suggested that local officials are more accountable than central government officials when it comes to identifying beneficiaries. He found that in Albania, decentralization improves targeting performance relative to centralized indicator targeting methods because local officials have access to household information otherwise not available to the central government. For example, local officials have access to information on additional income such as transfers and savings, not covered in questionnaires conducted by central government officials. Local people are also less likely to hide their assets when surveyed by local officials.

In addition, decentralizing identification of targeted beneficiaries to local officials grants more credibility to the identification strategy. Coady, Grosh, and Hoddinott (2004) conducted a meta-analysis of 111 targeted antipoverty programs across countries and found that, conditional on income level, targeting performance is better in countries with accountable governments as measured by people's voice.[3]

However, the accountability of local officials is less likely to hold when the possibility of local conflict is high, when local communities are heterogeneous or when mobility is free, as suggested by Seabright (1996). Since it is somewhat implausible to find homogenous local communities and free mobility, decentralization is prone to a significant downside: risk of capture by local elites (Galasso and Ravallion, 2005). Examining the Food for Education program in Bangladesh, Galasso and Ravallion (2005) found that communities with greater land inequality demonstrate a worse targeting performance than those with more equal land ownership. This suggests that local elites capture a bigger share of the benefits when the local poor are powerless.

Another case, among others, is found in the Social Fund investment projects in Ecuador. To test the existence of local elite capture in the project, Araujo et al. (2008) combined three datasets: village-level income distributions, Social Fund project administration, and province-level electoral results. They defined elite capture as a situation where the poor's choice of projects differs from those selected by that community. They found that after controlling for poverty, more unequal communities have a lower chance of receiving projects that provide in-demand private goods, such as latrines, to the poor.

The distribution of benefits could also be disturbed by an uneven political connections and social networks within a village, as suggested by Caeyers and Dercon (2012). They examined the targeting performance of food transfer programs in Ethiopia: Food For Work (FFW) and Free Food Delivery (FFD). They investigated the role of social networks and political connections on the

[3]Kauffman, Kraay, and Zoido-Lobaton (1999) create a composite measure consisting of aspects of political process, civil liberties, and political rights. This measure defines people's voice and provides indirect evidence of government accountability.

delivery of these food aid programs. Their findings suggest that households which are closely connected to high-level officials are 12% more likely to receive food aid than those that are not part of a strong "vertical" network.

In contrast, Rosenzweig and Foster (2003) observed that, in India, villages with a larger poor population are more likely to receive pro-poor projects. However, this only occurs in villages with elected village councils (*penchayats)*. This result does not hold in villages with more traditional leadership structures, suggesting that local democracy matters for whether the poor are benefited by decentralization.

In similar vein, Yamauchi (2010) did find significant influence of local elite capture on distribution of benefits of the IDT program in Indonesia, where poor villages were selected by the government to receive small business loans. She found that wealthier and more unequal villages were more likely to have better targeting performances than the poorer and more equal villages. Relatively poor households were more likely to receive more resources within wealthier and more unequal villages. This suggests that possible local elite capture might be diminished by the ease of identification of the poor in unequal villages.

2.2 The Indonesian Experience

Since 1997, the Indonesian government has implemented various targeting methods to identify beneficiaries for a host of social protection programs. The importance of targeting has been increasing, prompted by the relatively slow pace of poverty reduction during 2004–09, when the poverty rate decreased by less than 2% per annum (Alatas, Purnamasari, and Wai-Po, 2011). Reliable targeting methods were necessitated by the government’s fear of spikes in the national poverty rate following a significant reduction of fuel subsidies on several occasions since 2000.

Targeting performance in a broad range of social protection programs has been found to be inadequate. Sumarto, Suryahadi, and Widyanti (2010) found that many government programs suffer from loose targeting, resulting in poor coverage and leakage of benefits in practice. Scholarship programs for primary and secondary school students are among the programs with the lowest coverage rates. Both programs cover only about 5% of poor students, while the coverage of other programs ranges from 8 to 12% of the poor. The only program that does not have a coverage problem is Raskin. Instead, they found a large inclusion error; those who are nonpoor receive benefits. In 1999, Raskin targeted 10.9 million household beneficiaries, but the number of actual beneficiaries was almost double its original allocation of 20.2 million households.

In addition to this large inclusion error, Raskin also faces another significant leakage problem. Olken (2006) found that, on average, Raskin suffers from “missing rice”, amounting to 18% of the original allocation. This means that leakage in Raskin is attributuable to both corruption and imperfect targeting, where targeting contributed to about 80% of the leakage. Heterogeneity analysis suggests that areas with a more heterogeneous ethnic composition, less dense population, higher poverty rates, and fewer social organizations are less likely to receive the full amount of rice allocated to their areas.

Apparently, imperfect targeting has been the central problem behind the low targeting performance of social protection programs in Indonesia. A relatively recent study by Alatas, Purnamasari, and Wai-Po (2011) examined the targeting performance of three large antipoverty programs in Indonesia: Raskin*,* Jamkesmas (health insurance for the poor), and the BLT. They found rather similar results to those of a study by Sumarto, Suryahadi, and Widyanti (2002). Using the same database and household beneficiary targets, the three programs achieve different levels of coverage, with Raskin achieving the highest coverage, far higher than the intended allocation.

In spite of abundant evidence on the negative impact of elite capture on targeting performance, there is relatively little evidence of the existence of elite capture in Indonesia. According to Yamauchi (2010) and Alatas et al. (2013), in general, elite capture does not significantly affect the targeting performance of government social protection programs in Indonesia.

Using both field experiment and non-experimental data, Alatas et al. (2013) found that conditional on their consumption level, village elites and their relatives are more likely to receive targeted government welfare programs than non-elites. The probability of receiving benefits is higher if village elites hold formal leadership positions than if they only hold informal village leadership positions. Formal elite capture does not occur during the process of determining the beneficiaries; the elite capture occurs during the actual distribution.

III. THE PROGRAMS

3.1 Raskin (Rice for the poor)

Indonesia experienced a major economic crisis in 1997–98 due to the Asian financial crisis, leading to a contraction of the economy in 1998 by about 14%. A substantial devaluation of the rupiah caused a sudden and sharp increase in prices, especially of food, where nominal prices increased threefold. By the end of 1998, the poverty rate increased to 33% from merely 15% in mid-1997 (Bazzi and Sumarto, 2011). This hardship prompted the government to create an emergency social protection program called the Special Market Operation (OPK), which mainly aimed to protect the poor and prevent nonpoor households from falling below the poverty line by helping them to obtain affordable food.

The OPK program provided a hefty subsidy to the cost of rice, the principal staple food for most Indonesians. Every poor household was allowed to buy 10 kg of rice per month at a highly subsidized price of Rp1,000 per kg, which was far below the average market price of Rp3,000 per kg. This was a strategic program given that more than one fifth of total per capita expenditure among the poor in the late 1990s was allocated to rice consumption (Suryahadi et al., 2012).

The government only provided subsidized rice to households that belonged to the poorest demographic category at the time, which was later expanded to include households in the second poorest category as well.[4] In 1998, the program targeted 7.4 million households, which amounted to around 15% of households in the country (Sumarto, Suryahadi, and Widyanti, 2010). In 2009, the number of eligible households increased more than twofold to 19.1 million households.

The easing of the economic crisis in 2002 prompted the government to change the OPK program to become the “rice for the poor” (Raskin) program. The allocation of subsidized rice per poor household changed a few times; the program initially allocated 10 kg of subsidized rice per poor

[4]The welfare status of households was grouped into five categories starting from the lowest: Pre-prosperous households (KPS), prosperous I households (KS I), KS II, KS III, and KS III+. These categories, which were issued by the national family planning agency (BKKBN), were based on 23 indicators collected from the annual household census.

household but this amount later varied between 10 kg and 20 kg. During the period of our study, each poor household was allocated 15 kg of subsidized rice per month.

The actual distribution of the subsidized rice is decentralized. The state logistic agency, Bulog, allocates a certain quantity of rice, based on the number of poor households in a village, which can then be purchased by the local village authority. Bulog only distributes the rice up to the local distribution points. The local village officials then distribute it directly to poor households (Sumarto, Suryahadi, and Pritchett, 2003).

This method of distribution has a potentially crucial impact on the targeting performance of the program as this is the phase in which imperfect targeting might occur. Pressure from communities to enlist nonpoor households in the Raskin program, combined with reluctance among local administrators to get involved in conflicts, led to more equal distribution of rice (Sumarto, Suryahadi, and Pritchett, 2003; Hastuti et al., 2008).

3.2 BLT (Direct Cash Transfer)

In 2005, due to a sharp increase in world oil prices, the government decreased fuel subsidies resulting in increased gasoline (BBM) prices two times in less than a year, in March and October. In March, the subsidized gasoline price was increased by 30% from Rp1,800 (around USD 20 cents)/liter to Rp2,400 (around USD 26 cents)/liter. In October, it rose by more than 80% to Rp 4,500 (around USD 45 cents)/liter.

In addition, the subsidy on kerosene was also substantially reduced. These increases in fuel prices were deemed the main source of the 17% year-on-year inflation from February 2005 to February 2006 and the 8.7% month-on-month inflation during the course of three months from September to October 2005 (Bazzi and Sumarto, 2011).

To prevent poor and near-poor households from possible negative expenditure shocks caused by the reduced subsidy, the government introduced the first Direct Cash Transfer (BLT) program in October 2005. The government allocated Rp4,6 trillion (USD 460 million) for approximately 15.5 million households, or Rp100,000 (USD 10) for each household, which was distributed to poor households every three months for a year. This amount of money is equal to around 15% of an average household's annual expenditure (Bazzi, Sumarto, and Suryahadi, 2013).

Targeting of BLT recipients is conducted in several stages (Sumarto and Bazzi, 2011). The first step requires local government officials to list potential recipients in their respective regions. Second, using information from that list, enumerators from regional statistical agencies verify households enlisted. Finally, proxy-means testing is implemented to identify target households. Similar to Raskin, this seemingly ideal process to identify BLT recipients is far from ideal in practice. Only slightly more than half of the recipients admit to having ever been visited by enumerators, resulting in mistargeting (Hastuti et al., 2006).

While the identification process is similar to Raskin, the distribution phase of BLT is rather different. The distribution of BLT is centralized. The benefit is transferred and disbursed via local post offices and reaches virtually every village in the country. There is one post office in every subdistrict capital serving villages within. Local officials only have minimal influence on the process of determining eventual recipients.

3.3 Data Collection for Targeting

Since 2005, the government has been conducting a special household socioeconomic survey to identify target households. The first survey was called the 2005 Household Socioeconomic Survey (BPS PSE-05). Household poverty status in PSE-05 was used to determine target households for BLT and Raskin, in a process consisting of several stages. The following steps are taken from Hastuti et al. (2006). The first step requires enumerators to obtain data on poor households from the poverty census, local government data, and National Family Planning Coordination Agency (BKKBN). After visiting the local area unit (SLS) head, the enumerator is to investigate the poor households as directed.

The next step requires that enumerators conduct field verification, which includes direct observation and questioning of neighbors and local community figures. To identify eligible households, Statistics Indonesia (BPS) uses proxy means testing based on 14 welfare indicators.[5] To collect the data, the enumerator is supposed to interview the eligible households, in addition to observing houses. However, the practice was far from ideal; enumerators often skipped several steps. After visiting SLS head, enumerators often did not analyze and visit all poor households. Consequently, enumerators' assessments of the unvisited households might be based only on data from the visited households.

IV. CONCEPTUAL FRAMEWORK

Existing literature shows that elite capture could inhibit decentralized targeting from delivering the desired outcomes. In what conditions does elite capture materialize? Several studies demonstrate that elite capture is positively associated with inequality levels within communities—determined either by assets or income—especially when the local poor are powerless. In the remainder of this section, we explain the possible mechanisms through which the relationship between inequality and elite capture, which exists when local officials abuse their power to secure their own interests, could have consequences on targeting performance.

We begin with consequences of income or consumption inequality within communities. Given the relatively weak purchasing power of poor households, elevated purchasing power of nonpoor households allows them to buy new and more expensive assets that might attract people's attention. As a result, this makes the distinction between poor and nonpoor more obvious. In the context of decentralized targeting, a more unequal community implies a more convenient task for local officials in distinguishing which community members deserve benefits and which ones do not.

Unfortunately, this may prompt local officials to abuse their power. Abuse of power can take shape as early as the identification stage. As outlined in the previous section, an enumerator has to consult the SLS head regarding which poor households must be visited. An incumbent leader can give orders to an SLS head to direct the enumerators to households in which they have a personal interest.

[5]The indicators are: number of household members, floor area, broadest floor area type, broadest wall area type, toilet facilities, source of drinking water, main source of lighting, type of cooking fuel, frequency of meat/chicken/milk purchases per week, meal frequency of usual family members per day, frequency of new clothes purchases by household members per year, access to treatment at community health center or polyclinic for family members, main field of work of household head, highest level of education of household head, and assets of more than USD 50.

More explicit cases of abuse of power could occur in the distribution stage as well, especially in the case of Raskin, where an incumbent leader has the power to direct local officials to distribute the benefits to particular households. A leader sees the poor as a pool of potential voters, and, as such, they do not want to lose potential electoral support. When some poor households do not receive either Raskin or BLT or both, they might put the incumbent under suspicion and opt not to vote for him or her in the next election, thus jeoparizing the leader's election prospects.

This hypothetical motivation implies that an increase in inequality will lead to a better targeting performance since the incumbent will make sure the majority, if not all, of poor households in the community receive benefits. However, this does not rule out the possibility of some poor households being left behind and some nonpoor households being included. Inequality could give elites the institutional power to allow the benefits of public programs to be accrued by the most favored (Ali, 2007).

Mulyadi's research (2013) provides supporting evidence for our hypothesis. His extensive fieldwork demonstrates that Raskin and BLT have been taken advantage of by local leaders nationwide. He demonstrated that, for example, head of the *kabupaten* abuse their power over both programs by rewarding their voters and retaining their loyal affiliates to secure their office in the next elections.

V. DATA SOURCES

5.1 Data and Descriptive Statistics

To analyze the impact of inequality on targeting performance, we use the 2009 National Socioeconomic Household Survey (Susenas) and 2008 Village Potential Survey (Podes). Susenas is a nationally representative household survey conducted annually covering over 200,000 households and 800,000 individuals. Its sample coverage only enables Susenas to represent Indonesia at the *kabupaten* level.

Susenas provides detailed information on the characteristics of households and individuals, enabling us to identify poor households based on per capita consumption levels. Susenas also collects information on government protection programs. The 2009 Susenas asked households whether they had received BLT in 2008/2009 and whether they had bought subsidized rice in the last three months. Combining information on household poverty status with the actual distribution of BLT and Raskin, we can estimate targeting performance in both programs by looking at each program's rate of exclusion and inclusion errors. We also use Susenas to create our key explanatory variable, the Gini ratio, to measure inequality. These household-level variables are then aggregated at the *kabupaten* level.

In comparison to PSE-05, Susenas is better in terms of identifying target household beneficiaries for Raskin and BLT. Susenas allows us to obtain consumption expenditure per capita to identify potential target household beneficiaries, whereas PSE-05 only allows researchers to proxy household consumption expenditure per capita using the 14 household welfare indicators.

The second dataset, Podes, is a village census conducted three times in every decade, covering more than 60,000 villages in Indonesia. It collects detailed information on village characteristics such as size, population, infrastructure, geographic location, crime statistics, and other village-level information. Most of this information is collected from official village documents and interviews with relevant village officials. We use Podes to create control variables at *kabupaten* level consisting of variables measuring access, social capital and network, democracy, and population density.

Our main analysis uses variables created from Susenas merged with those from Podes at the *kabupaten* level. The final sample pool consists of 465 *kabupaten* with nonmissing variables. Table 1 shows summary statistics of outcome and control variables at *kabupaten* level. The exclusion error of BLT is higher than that of Raskin. On the other hand, the inclusion error of Raskin is higher than that of BLT, implying a higher number of nonpoor households receive Raskin than BLT.

Table 1. Summary Statistics

Variable	N	Mean	SD
Outcome variables:			
Inclusion error rate of BLT	471	0.492	0.148
Inclusion error rate of Raskin	466	0.545	0.140
Exclusion error rate of BLT	471	0.529	0.193
Exclusion error rate of Raskin	471	0.348	0.231
Independent Variables:			
Gini ratio	471	0.291	0.042
Raskin recipients	471	0.488	0.236
BLT recipients	471	0.324	0.196
Poverty rate	471	0.151	0.106
Slum areas	465	0.080	0.147
Religious activities	465	0.908	0.153
Non-governmental organization	465	0.216	0.177
Ethnicities > 1	465	0.762	0.221
Asphalt roads	465	0.626	0.295
Good roads	465	0.881	0.193
Good cell phone signal	465	0.866	0.229
House ownership	471	0.792	0.127
Electrification	471	0.762	0.265
Health insurance for the poor	471	0.307	0.177
Village Head educated to senior high school or higher	465	0.735	0.213
People do not trust local government	471	0.197	0.104
Density (100 persons per hectare)	465	9.913	21.884
Working in agriculture	471	0.350	0.222
Working in formal sector	471	0.214	0.098
Net enrollment rate at elementary school	471	0.931	0.081
Net enrollment rate at junior high school	471	0.652	0.129
Net enrollment rate at senior high school	471	0.463	0.136
Educational attainment beyond senior high school	471	0.233	0.104

Source: Podes 2008 and Susenas 2009.
Note: N = Number of *kabupaten*.

5.2 Program Recipients

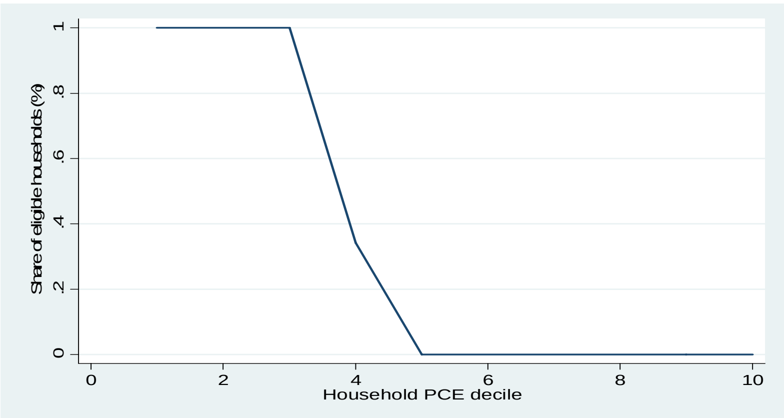
To determine household beneficiaries of BLT and Raskin, the government standardizes the cost of living across regions in Indonesia. To be consistent with the government's definition we calculate the following:

$$SPCE(h,d) = \frac{PCE(h,d)}{[PL(DKI)/PL(d)]} \qquad (1)$$

where *SPCE(h,d)* denotes standardized per capita expenditure of household *h* in district (*kabupaten*)*d*, *PCE(h,d)* denotes nominal per capita expenditure of household *h* in district *d*, *PL(DKI)* denotes poverty line of the capital DKI Jakarta, and *PL(d)* denotes the poverty line of district *d.* After obtaining the standardized per capita expenditure, we pick the bottom 19.1 million households, which was the official government number of household beneficiaries for Raskin and BLT in 2009, as our main sample pool. Our sample represents about 32% of all households.

Figure 1A shows that the poorest 40% of households were eligible for benefits. Median and richer households were not listed. However, Figure 1B clearly shows that mistargeting occurred in both BLT and Raskin programs; even the richest (10th decile) households received benefits. The proportion of households that received Raskin is bigger than those who received BLT at every decile.

A. Eligibility



B. Actual

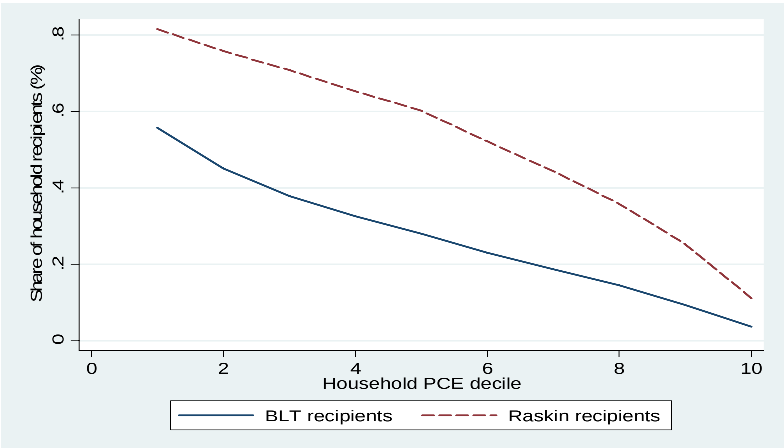


Figure 1. Distribution of BLT and Raskin recipients by decile of household per capita expenditure (standardized to DKI per capita expenditure)

VI. EMPIRICAL STRATEGY AND ESTIMATION RESULTS

6.1 Empirical Strategy

In order to analyze the impact of inequality on targeting performance, we estimate the following equation at *kabupaten* level:

$$Y_i = \beta_0 + \beta_1 GINI_i + \beta_2 X_i + \varepsilon_i \qquad (2)$$

where Yi denotes targeting performance, measured by rates of inclusion and exclusion error, of BLT and Raskin in *kabupaten i*. Our main independent variable is $GINIi$ which denotes Gini ratio in kabupaten *i*. The impact of Gini ratio on inequality is controlled by including **X** which is a vector of *kabupaten*-level variables that might affect targeting performance, such as poverty rates, proportion of slum areas in a district, educational attainment of village heads, existence of religious activities, existence of non-governmental organizations, road quality, ethnic diversity, electricity availability, and other relevant variables. Error term in *kabupaten i,* which is assumed to be independent across districts, is denoted by ε_i. We hypothesize that an increase in inequality will translate to better targeting performance. Thus, we expect $\beta_1 < 0$ if our hypothesis is correct.

6.2 Results

Table 2 presents the results of BLT and Raskin in terms of targeting performance. We divide the main results into four columns. The first two columns give the estimated effects on the inclusion error of BLT and Raskin. We find that inequality is not related to the inclusion error in either program as both coefficients are statistically insignificant. However, a lower inclusion error is found in communities with higher poverty rates. This relationship is significant in both BLT and Raskin programs.

Table 2. The Determinants of Targeting Performance of BLT and Raskin

	Inclusion Error				Exclusion Error			
	BLT (1)		Raskin (2)		BLT (3)		Raskin (4)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Gini ratio	0.018	0.103	0.116	0.116	-0.550**	0.150	-0.496*	0.204
Poverty rate	-1.399**	0.065	-1.416**	0.076	-0.136	0.092	-0.001	0.142
Slum areas	0.048	0.044	0.014	0.034	0.035	0.051	-0.130	0.067
Religious activities	-0.077*	0.032	-0.051	0.036	0.041	0.034	-0.174*	0.072
NGOs	0.093**	0.036	0.041	0.036	-0.046	0.042	0.097	0.070
Ethnicities	-0.015	0.022	-0.018	0.021	-0.008	0.029	0.118**	0.044
Asphalt roads	-0.012	0.023	-0.010	0.023	0.020	0.029	0.088	0.049
Good roads	0.062	0.042	0.093*	0.042	0.171*	0.072	-0.147	0.077
Good cell phone signal	-0.077*	0.039	-0.047	0.038	0.122**	0.045	-0.048	0.076
House ownership	0.019	0.050	0.092*	0.042	0.068	0.062	-0.398**	0.090
Electrification	-0.091**	0.032	-0.063	0.033	-0.057	0.033	-0.216**	0.072
Health insurance for the poor	0.082*	0.036	-0.028	0.048	-0.494**	0.047	-0.282*	0.114
Village Head educated to senior high school or higher	-0.085**	0.032	-0.060	0.032	0.095**	0.036	-0.143*	0.059
People's trust in local government	0.109	0.059	0.050	0.060	-0.017	0.072	0.129	0.117
Density	-0.001*	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
Raskin recipients	0.017	0.030			-0.205**	0.042		
BLT recipients			0.173**	0.060			-0.466**	0.128
Constant	0.845**	0.068	0.703**	0.069	0.597**	0.093	1.456**	0.154
Observations	465		464		465		465	
R-squared	0.639		0.627		0.708		0.439	

*Significant at 5 %.
**Significant at 1%.

On the other hand, inequality has a significant and substantial relationship with the exclusion error of BLT and Raskin. Column (3) shows that an increase of 0.01 or 1 percentage point in Gini ratio is associated with a reduction of 0.55 percentage point in exclusion error of BLT. This implies that the change in exclusion error in BLT is highly sensitive to the change in inequality level. Meanwhile, Column (4) shows that a 1 percentage point increase in Gini ratio is associated with a reduction of 0.50 percentage point in exclusion error of Raskin.

We can draw two important inferences from these results. First, a significant negative association between inequality and exclusion error in BLT and Raskin, together with an insignificant association between rate of inclusion error and inequality in both programs, suggests the existence of elite capture in both programs.

This can be explained by potential abuse of power by incumbent leaders aiming to retain their positions. To collect more votes and, hence, increase the probability of winning the next election, the incumbent leader would increase their popularity by lowering the proportion of poor households not receiving BLT or Raskin or both, while retaining some nonpoor households as beneficiaries. This practice is easier in communities with higher levels of inequality where identification of poor and nonpoor households is easier. Bardhan and Mookherjee (2000) suggested that in the context of decentralization, elite capture is found to be higher in high-inequality districts and lower in districts with low inequality levels. Indeed, this trend has been shown to apply in the case of Indonesia (Mulyadi, 2013).

The second inference from the results is that elite capture is more extensive in Raskin than in BLT. This is suggested by the fact that in more unequal communities, given the same number of beneficiaries, a lower exclusion error implies a bigger proportion of nonpoor households receive benefits they are not supposed to receive, suggesting a larger magnitude of elite capture in Raskin than in BLT.

More pronounced occurance of elite capture in Raskin than in BLT makes sense for two reasons. First, local administrators have more power to determine who receives Raskin benefits. Local administrators tend to distribute subsidized rice equally to poor and nonpoor households to avoid getting involved in conflicts (Hastuti et al., 2008; Pritchett, Sumarto, and Suryahadi, 2002). On the other hand, local administrators only have limited power to determine who receives BLT. The central government delivers the cash payment through the nearest postal offices; local officials only distribute cards to disburse the cash to beneficiaries.

Second, the monetary value of BLT is arguably higher compared to Raskin, which gives more motivation for poor households to ensure the distribution of benefits is accurate. The consequence of inaccuracy in eventual BLT recipients can be detrimental in a wider sense. Cameron and Shah (2012) find that worse targeting performance in BLT causes a higher rate of crime in communities. The impact on crime is more robust and higher when nonpoor households receive the benefit than when poor households miss out on the benefit.

Overall, our results generate similar conclusions to those of a study by Alatas et al. (2013). The evidence of elite capture is found in the distribution phase of government programs, not during registration of beneficiaries since verification data for both potential BLT and Raskin recipients is drawn from the same database, PSE-05. Nevertheless, our results should only be considered as indirect evidence of elite capture since our data does not have information on the relationship between beneficiaries and local administrators.

VII. HETEROGENEITY ANALYSIS

In this section, we investigate the heterogeneity impacts of inequality on targeting performance by level of inequality, educational attainment, and location. In addition, we also perform a robustness test on the measure of inequality using the Palma ratio in lieu of the Gini ratio.

7.1 Level of Inequality

Table 3 shows the results when we split the observations into high and low inequality *kabupaten*. The results confirm that the higher the inequality level within communities, the bigger the impact on targeting performance. In highly unequal communities (Panel A), the Gini ratio is higher than the median, 0.28. Columns (3) and (4) of Panel A show that the impact of inequality on the exclusion error is higher in BLT than in Raskin. The magnitude is greater than the general results in Table 2.

In highly unequal communities, a 1 percentage point increase in Gini ratio is associated with a reduction of 0.90 percentage point in exclusion error of BLT, but only 0.73 percentage point in Raskin. In communities with a Gini ratio lower than the median, inequality only has a significant impact on exclusion error in BLT as shown in Column (3) of Panel B. The magnitude is lower than in highly unequal communities.

Table 3. The Determinants of Targeting Performance of BLT and Raskin by Level of Inequality

	Inclusion Error				Exclusion Error			
	BLT (1)		Raskin (2)		BLT (3)		Raskin (4)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Panel A: Above Median								
Gini ratio	-0.225	0.218	-0.202	0.227	-0.901**	0.252	-0.773*	0.388
Full control variable	Yes		Yes		Yes		Yes	
Constant	0.858**	0.124	0.779**	0.118	0.864**	0.143	1.612**	0.250
Observations	232		232		232		232	
R-squared	0.596		0.596		0.711		0.432	
Panel B: Below Median								
Gini ratio	0.246	0.255	0.157	0.229	-0.786*	0.370	0.087	0.534
Full control variable	Yes		Yes		Yes		Yes	
Constant	0.887**	0.098	0.701**	0.094	0.515**	0.138	1.321**	0.218
Observations	232		231		232		232	
R-squared	0.725		0.715		0.743		0.463	

*Significant at 5 %.
**Significant at 1%.

7.2 Educational Attainment

Bardhan and Mookherjee (2000) suggested that elite capture is more prevalent in communities with a higher illiteracy rate. They argue that literacy is associated with political awareness and a disparity in awareness levels across classes. We investigate whether this applies in Indonesia as well. We test this proposition by running two regressions of Equation (2). The first regression is conducted in communities with high educational attainment, where the proportion of people educated beyond senior high school is higher than the median, 0.20. The second regression is conducted in districts where the proportion of people educated beyond senior high school is lower than the median. The results are shown in Table 4.

Unlike our general results, Columns (3) and (4) of Panel A demonstrates that the impact of inequality on exclusion error is bigger in Raskin than in BLT when average educational attainment within communities is higher than the median. These results imply that more educated communities tend to be able to identify mistargeting in Raskin and set it right. On the other hand, inequality is significantly and positively associated with inclusion error in Raskin in communities with average educational attainment lower than the median, as shown in Column (2) of Panel B.

Table 4. The Determinants of Targeting Performance of BLT and Raskin by Level of Educational Attainment

	Inclusion Error				Exclusion Error			
	BLT (1)		Raskin (2)		BLT (3)		Raskin (4)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Panel A: Above Median								
Gini ratio	-0.167	0.163	-0.036	0.170	-0.664**	0.196	-0.755**	0.272
Full control variable	Yes		Yes		Yes		Yes	
Constant	0.844**	0.114	0.653**	0.124	0.476**	0.135	1.720**	0.234
Observations	233		233		233		233	
R-squared	0.598		0.583		0.759		0.513	
Panel B: Below Median								
Gini ratio	0.198	0.116	0.384**	0.132	-0.220	0.203	-0.560	0.323
Full control variable	Yes		Yes		Yes		Yes	
Constant	0.734**	0.091	0.670**	0.097	0.712**	0.119	1.015**	0.220
Observations	231		230		231		231	
R-squared	0.748		0.723		0.684		0.403	

*Significant at 5 %.
**Significant at 1%.

7.3 Urban/Rural Location

Table 5 displays the impacts of heterogeneity of inequality on targeting performance by urban or rural location. Column (1) of Panel A shows that the inclusion error in BLT is negatively related with higher inequality levels in urban areas with a magnitude as big as 0.62, while the impact on the exclusion error is even higher at 0.76, as shown in Column (3). However, inequality does not affect targeting performance in Raskin. Together, this implies that the targeting performance of BLT is much better than that of Raskin, suggesting lower elite capture in BLT in urban areas. On the other hand, in rural areas, Panel B shows inequality negatively affects exclusion error rate only in BLT. The magnitude is lower than in urban areas implying greater elite capture in BLT in rural areas.

Table 5. The Determinants of Targeting Performance of BLT and Raskin by Location

	Inclusion Error				Exclusion Error			
	BLT (1)		Raskin (2)		BLT (3)		Raskin (4)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Panel A: Urban								
Gini ratio	-0.619*	0.296	-0.346	0.268	-0.766**	0.295	-0.848	0.473
Full control variable	Yes		Yes		Yes		Yes	
Constant	1.135**	0.254	0.630**	0.203	1.333**	0.334	2.830**	0.425
Observations	95		95		95		95	
R-squared	0.673		0.711		0.655		0.668	
Panel B: Rural								
Gini ratio	0.059	0.103	0.123	0.125	-0.446**	0.165	-0.377	0.232
Full control variable	Yes		Yes		Yes		Yes	
Constant	0.788**	0.074	0.724**	0.078	0.567**	0.104	1.180**	0.183
Observations	370		369		370		370	
R-squared	0.674		0.639		0.694		0.395	

*Significant at 5%.
**Significant at 1%.

7.4 Robustness Check

To test the robustness of our results, we conduct another regression using an alternative measure of inequality, the Palma ratio. This measure has gained popularity because it is easier to interpret than the conventional Gini ratio.[6] Compared to the Gini ratio, which is more sensitive to changes in the middle of the distribution, the Palma ratio is more focused on the extreme tails (Cobham and Sumner, 2013). Using different types of inequality measurements can offer consistency checks of inequality impact on targeting performance.

Table 6 shows the regression results using the Palma ratio as the inequality measure. The results are similar to the results in Table 2 and imply that inequality significantly affects the exclusion error but not the inclusion error and affects BLT more than Raskin. This indicates that our previous estimation results are robust to the measure of inequality used.

[6] Palma ratio indicates the inequality between the share of income of the richest 10% and the poorest 40% (Cobham and Sumner, 2013).

Table 6. The Determinants of Targeting Performance of BLT and Raskin–Palma Ratio

	Inclusion Error				Exclusion Error			
	BLT		Raskin		BLT		Raskin	
	(1)		(2)		(3)		(4)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Palma ratio	-0.016	0.018	0.004	0.021	-0.094**	0.025	-0.079*	0.034
Poverty rate	-1.396**	0.065	-1.411**	0.076	-0.142	0.090	-0.009	0.143
Slum areas	0.051	0.044	0.016	0.034	0.034	0.051	-0.131*	0.066
Religious activities	-0.078*	0.032	-0.052	0.036	0.043	0.033	-0.172*	0.072
NGOs	0.098**	0.036	0.045	0.036	-0.048	0.042	0.093	0.069
Ethnicities	-0.014	0.022	-0.017	0.021	-0.008	0.029	0.118**	0.044
Asphalt roads	-0.010	0.023	-0.008	0.023	0.020	0.029	0.087	0.049
Good roads	0.061	0.043	0.093*	0.042	0.166*	0.072	-0.151	0.078
Good cell phone signal	-0.081*	0.039	-0.050	0.038	0.121**	0.045	-0.047	0.077
House ownership	0.014	0.050	0.087*	0.042	0.072	0.062	-0.393**	0.090
Electrification	-0.093**	0.032	-0.065*	0.033	-0.057	0.033	-0.216**	0.072
Health insurance for the poor	0.084*	0.036	-0.026	0.049	-0.492**	0.047	-0.283*	0.115
Village Head educated to senior high school or higher	-0.088**	0.032	-0.063	0.033	0.094**	0.036	-0.143*	0.059
People's trust in local government	0.109	0.059	0.051	0.060	-0.024	0.072	0.122	0.118
Density	-0.001*	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
Raskin recipients	0.015	0.030			-0.204**	0.042		
BLT recipients			0.170**	0.060			-0.462**	0.129
Constant	0.875**	0.064	0.739**	0.065	0.541**	0.085	1.396**	0.147
Number of observations	465		464		465		465	
R-squared	0.639		0.626		0.709		0.438	

*Significant at 5 %.

**Significant at 1%.

VIII. CONCLUSION

Due to the existence of elite capture, decentralized targeting in government social protection programs does not generate the best outcomes in Indonesia. Programs with more centralized targeting methods are able to deliver a better performance. Our main analysis finds that higher inequality reduces the exclusion error, but has no impact on the inclusion error. BLT, which has a centralized targeting process, has a higher inequality elasticity of exclusion error than Raskin, which has a decentralized targeting mechanism.

We interpret the results as indirect evidence of the existence of elite capture, which is greater in Raskin than in BLT. Given a certain number of household beneficiaries, the lower the exclusion error, the smaller the elite capture because this implies the local administrators minimize the number of nonpoor households enlisted for BLT or Raskin. Additionally, we also find heterogeneity in the impacts by inequality level, educational attainment, and urban/rural location.

Our results indeed show that inequality plays an important role in reducing exclusion errors, that is, the proportion of poor households not receiving BLT or Raskin. This is because higher inequality levels within communities makes identification of the poor easier and, therefore, leads to a higher probability of better targeting performance.

This finding implies that to achieve more accurate targeting, special efforts to reduce inclusion errors are required. Better identification of the poor does not automatically lead to a reduction in inclusion error. Furthermore, stricter supervision in the distribution of government social protection benefits needs to be enacted in more equal communities as they are more prone to capture by local elites. An avenue for future research is to investigate whether local leaders of districts demonstrating a lower exclusion error succeed in being reelected.

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