Community-Based Targeting and Initial Local Conditions: Evidence from Indonesia's IDT Program

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I. Introduction

Recently, there has been a growing interest in the integration of community involvement in the provision of social programs.[1] With the distribution of program benefits, a decentralized, community-based selection of beneficiaries is considered to be less costly and more accurate. This is because local agents, such as community officials and social organization members, have better information relative to the central government about who deserves assistance within the community (Alderman 2002; Faguet 2004). However, much anecdotal evidence points to the possibility that local nonpoor elites capture program resources, particularly in communities with large economic inequality.[2] Theory also suggests that the degree of capture can depend on local contexts, including the political influence of different groups, which, in turn, hinges on the political awareness and socioeconomic status of such groups (Bardhan and Mookherjee 2000, 2005). The lack of administrative capability among local agents can also offset the information advantage.[3] It is unclear how much, in what kind of settings, and at which stages of program implementation these factors limit the effectiveness of community-based targeting. A meta-analysis of targeted antipoverty programs indicates that the performance in allocating benefits to the poor varies even within programs adopting

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[1] See, e.g., World Bank (2000, 2004) and Mansuri and Rao (2004).

[2] For example, Dreze and Sen (1989) point to possibly undesirable allocations of relief when the poor are powerless within communities. Numerous descriptive studies report consistent evidence (e.g., Crook and Manor 1998; Conning and Kevane 2002; and Antlov 2003).

[3] See, e.g., Conning and Kevane (2002) and Coady, Grosh, and Hoddinott (2004).

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the same scheme of community-based targeting (Coady et al. 2004). This suggests the importance of investigating local factors that might explain this variance.[4] Nevertheless, relatively few studies have investigated community characteristics correlated with targeting performance, particularly changes in targeting performance over time.

This article fills this gap by providing evidence on the relationship between targeting performance and a rich array of preprogram community conditions, such as the levels of poverty and inequality, density, characteristics of local leaders and local government, and the availability of infrastructure. In particular, I exploit the panel information on the targeting performance of Indonesia's antipoverty program, *Inpres Desa Terttingal* (IDT 1994–97). Under this program, the government selected poor villages for funding that was designated for small business loans. In turn, these selected poor villages then chose households eligible for loans according to their own criteria. Results show that the wealthier and more unequal villages constantly targeted well. This suggests that inequality is not always associated with elite capture. The positive association between inequality and targeting might reflect Indonesia's political context, where village heads had incentives to follow the national guidelines to target the poor. Evidence is also found that villages with a high population density and young, educated heads initially exhibit better targeting but that they then lose this advantage as the village heads become less involved in the monitoring of benefit allocation.[5]

These findings relate to the growing literature on targeting. A number of cross-sectional studies have provided mixed evidence on the relationship between targeting and the levels of income and inequality. On the one hand, Coady et al. (2004) find that richer and more unequal countries target well, which is consistent with my findings. On the other hand, in Bangladesh's Food-for-Education program, villages with higher inequality in landholding attain a lower participation rate for the poor compared to the nonpoor, and

[4] Jayne et al. (2001) also find a large variation in the allocation pattern across different regions in Ethiopia in that country's food aid/food-for-work programs.

[5] IDT involved geographic targeting based on proxy means testing as well. In order to focus on the heterogeneity in community-based targeting, this article mainly studies the within-village distribution of program benefits. The effectiveness of geographic targeting is investigated in a number of studies (e.g., Glewwe 1992; Baker and Grosh 1994; Bigman et al. 2000; Bigman and Srinivasan 2002; Schady 2002; and Elbers et al. 2007). Also, Skoufias, Davis, and de la Vega (2001) and Coady (2006) evaluate targeting outcomes under PROGRESA, which used geographic targeting jointly with other targeting schemes.

poorer villages show a lower participation rate for the nonpoor (Galasso and Ravallion 2005).[6]

These cross-sectional studies do not address whether targeting performance changes and which local conditions are associated with the changes.[7] A few exceptions include a study by Ravallion (1999), which shows that a reduction in the program budget worsened targeting performance in Argentina. Bardhan and Mookherjee (2006) explore how targeting outcomes change when poverty, inequality, and political competition change within villages. They find that targeting deterioration is associated with increased land inequality in an employment generation program but not in credit and agricultural minikit programs. Given these findings, they conclude that the administration of local public good programs is more likely to involve capture due to its less transparent nature. My results are consistent with this view: under IDT, where the benefits are private goods, little evidence is found for a link between within-community inequality and poor targeting.

Relatively limited evidence is available for the relationship between targeting and the characteristics of local leaders. Related studies indicate that it is important to monitor or regulate the actions of those leaders. For example, Coady et al. (2004) find that countries that are more accountable exhibited better targeting. Olken (2007) shows that monitoring by the national government agency reduced corruption in local infrastructure projects. Ravallion (2000) reports that within-province targeting improved after a set of rules on implementation and targeting was provided by the central government together with a larger budget. Numerous case studies report that monitoring by, and involvement of, upper-level government is associated with better out-

[6] In the related literature on the community-based choice of public projects, Araujo et al. (2008) report that inequality is correlated with a lower probability of receiving propoor projects such as latrines. In another study on corruption, Olken (2006) shows that Indonesian districts with higher ethnic fragmentation and lower density have more subsidized rice go missing before it reaches the intended beneficiaries, as compared to other districts. However, the median per capita expenditure and within-district inequality are not significantly correlated with the degree of corruption.

[7] Some studies examine changes in inter- and within-community targeting performance, but the lack of data often precludes the investigation of local factors associated with within-community targeting. For example, Park, Wang, and Wu (2002) report that the targeting of poor counties under China's *qiba* program deteriorated over time, but the within-county distribution is unknown. Stifel and Alderman (2005) show the changes in inter- and intra-district targeting under Peru's *Vaso de Leche* transfer program, but the factors related to these changes are not examined. Also Jayne et al. (2002) investigate the relationship between current and past receipt of program resources. They find that some households are chronic beneficiaries, which suggests the possibility of aid dependence.

comes.[8] My findings are in line with these. Villages with young, educated heads demonstrated better targeting performance only in the initial year, when the heads directed the selection of eligible households. Later, when the heads were not involved in the allocation of benefits among the eligible, the initial advantage disappeared.

The rest of this article is organized as follows: Section II describes IDT more fully, and Section III explains the data and targeting measures used in the analysis. Following the illustration of the empirical strategy in Section IV, Section V discusses the results for overall targeting performance. Section VI presents the results for changes in targeting performance, and Section VII concludes.

II. Antipoverty Program for Left-Behind Villages, IDT

A. The Scope and Implementation Process of IDT

Inpres Desa Terttingal (IDT) was launched by the Indonesian government to strengthen the income-generating power of poor households in disadvantaged communities, which were deemed as being left behind during the economic growth of the 1970s and 1980s. The government provided these selected poor villages with grants designated for loans for productive investment. The central government first identified poor villages using a formula-based welfare indicator called a "village score." Selected villages were then allowed to identify households eligible for a loan. In order to encourage the use of local knowledge of the residents' well-being, the central government simply instructed selected villages to target "poor people who live in a village," without imposing any selection criteria. A village head and a local government agency called *Lembaga Ketahanan Masyarakat Desa* (LKMD [village community resilience board]) were assigned to facilitate the selection of poor households (Badan Pusat Statistik 1994).

The scope of IDT is considerable. Each selected village received Rp. 20 million (approximately US$8,932) per annum.[9] With approximately one-third of Indonesia's more than 60,000 villages funded for 3 fiscal years, government spending on the program totaled over Rp. 1.2 trillion (US$536 million). IDT also achieved relatively wide coverage. Among selected villages, 34% of households had received at least one IDT loan by the end of the program period, 1994–97. This figure corresponds to 13% of all Indonesian households. The

[8] For examples, see Parry (1997), Wade (1997), and Johnson, Deshingkar, and Start (2005). Another set of related studies on local governance suggests that political competition does not matter in within-village targeting (Bardhan and Mookherjee 2006), and the evidence on the effect of local democracy is mixed (Rosenzweig and Foster 2003; Olken 2008).

[9] This is based on the 1995 average exchange rate of Rp. 2,239 per 1995 U.S. dollar (Indonesian Financial Statistics, Bank Indonesia).

average per household grant size was Rp. 166,287, which was four times the average monthly household per capita expenditure (PCE) in selected villages. Since not all the households received a loan, the cumulative loan size among participants was larger, averaging Rp. 467,593. This was about 11 times the average monthly household PCE among households in selected villages and 13 times the PCE among participating households (appendix table A1).[10]

In order to select poor villages, a village score was computed based on the availability and quality of infrastructure and the living standard of residents. A village was designated as poor, and thus received the grant, if its score was below the provincial threshold.[11] As the village score formula was modified in the second year of the program, some villages were added to the funding list. While most villages funded in the first year continued to receive funding regardless of the second year's village score, a minor fraction of the villages with a very small number of households ceased to receive grants based on a concern that the across-village differences in the per capita grant value were too large (Badan Pusat Statistik 1995). My community-based (within-village) analysis uses villages that were funded at least once, and it controls for the process of village selection.

Within selected villages, eligible households were identified and formed into groups.[12] They were required to submit project proposals to the village head and then to the subdistrict government. Upon approval, the groups received funds directly through a local branch of a state-owned bank, and they were responsible for loan management.[13] Most eligible households (84%) participated in the program.

Prior to the start of IDT, there was wide concern about the local ability to implement the program because it was a departure from the centralized approach (Booth 1994). After the 3-year program period, IDT was followed by a similar community-based scheme called the Kecamatan Development Program (Daley and Fane 2002), and there has been an ongoing call for continuing targeted poverty alleviation and a community-based development approach (World Bank 2006).

[10] Author's calculation based on the SUSENAS 1997. The per household grant size is based on the number of households in the 1993 PODES.

[11] In the initial year, two thresholds were used. A village was funded if its score was below the lower of the two thresholds, and it was not funded if it was above the higher threshold. If the score was between the two thresholds, the funding status was determined by the local field officer.

[12] Groups were sometimes based on the geographic location of eligible households and on existing organizations such as farmers' groups and other occupational groups (Perdana and Maxwell 2004).

[13] Detailed management schemes such as interest rates and repayment cycles were determined in each group, and the information underlying these decisions is unknown to researchers.

B. Previous Studies on IDT

The availability of nationally representative data and the explicit formula-based village selection rule have attracted many researchers to investigate the inter-village distribution of IDT funds. However, the within-village distribution and the association with the local conditions have not yet been investigated. Studies on the inter-village distribution of IDT funds find that the rules to select poor villages were closely followed and involved few errors (Alatas 2000) and that districts with a lower level of average PCE had a larger number of IDT villages (Daimon 2001).[14]

The impact of IDT has also been analyzed, with different identification strategies resulting in mixed findings. On the one hand, the results based on matching methods indicate few effects. Molyneaux and Gertler (1999) use the propensity-score-matching and village fixed effects model, and they find no significant effects on a number of outcomes, such as labor supply and household expenditure. Using a different matching method based on the differential probability of funding across provinces, Alatas (2000) reports positive effects in rural areas on household consumption, self-employment activities among spouses, and work among children. However, once province-level fixed effects are incorporated, no effect is found for consumption, and the results for labor supply are not reported. Alatas (2000) also conducts a regression discontinuity analysis based on the second year rules. The comparison between villages whose score was just below and above the provincial threshold indicates varying effects across provinces.[15]

On the other hand, studies using the variation in per capita/household grant value find significant negative effects on poverty and inequality for at least some of the villages. Larger per capita grants were correlated with a decline or slower growth in within-province inequality (Akita and Szeto 2000). In villages that initially had some economic infrastructure, larger per household grants were associated with disproportionate increases in village-level average consumption (Yamauchi 2008).[16] Some of the heterogeneity in the impact of IDT might be related to the differences in targeting performance across villages. This study addresses this issue by investigating the relationship between within-village targeting outcomes and initial village conditions.

[14] This does not mean that the IDT's village selection rules were perfect. For instance, case studies from two provinces indicate the possibility that geographic targeting omitted some poor households residing outside the IDT villages (Sumarto et al. 1998; Perdana and Maxwell 2004).

[15] Interviews conducted in six provinces also indicated that participants there found that IDT loan activities were not very profitable (Badan Pusat Statistik 1997).

[16] No impact is found for the incidence of child labor in rural areas (Yamauchi 2007). In an overview of major antipoverty credit programs in the 1990s, Sumarto et al. (1998) conclude that IDT was relatively flexible and that loan management responsibility shared among beneficiaries encouraged production activities.

III. Data and Targeting Performance

A. Data

My empirical analysis uses the following three data sets. First, information on IDT benefits and household characteristics is extracted from the 1996 and 1997 National Socioeconomic Household Survey (SUSENAS)—a nationally representative, cross-sectional survey of households. Second, 1993 Village Potential Statistics (PODES), a village-level census, provides information on village characteristics observed before IDT started. Third, village- and year-specific funding status is available in the IDT administrative data set. I combine these data sets and focus on rural areas, which include most of the funded villages.[17]

Targeting measures are based on a household's predicted poverty level and its actual program benefits. First, the household poverty level is defined using predicted household per capita expenditure (PCE). The predicted PCE is used because the actual PCE could be changed as a result of receiving IDT loans.[18] I use 1993 and 1994 SUSENAS to regress PCE on provincial fixed effects and a number of household characteristics.[19] Applying the coefficients from this regression to the same variables in the 1996 and 1997 SUSENAS, I predict the PCE that is likely to proxy the poverty level not affected by the program.[20]

[17] I do not pool rural and urban areas because they faced distinct criteria for the identification of poor communities, and they are likely to have different sets of unobserved community attributes. The PODES and the IDT data are combined with the SUSENAS based on the village ID. The share of rural villages that are matched is 90% for 1996 and 89% for 1997.

[18] Also expenditure rather than wealth is used to indicate household poverty levels because the SUSENAS does not contain information on assets except for housing. Retrospective information on consumption or income is also unavailable.

[19] See appendix table A4 for the results and appendix table A2 for the summary statistics for household-level characteristics. All expenditure and loan values are adjusted for inflation and expressed in terms of 1995 prices. The province-specific price index collected by Statistics Indonesia (formerly called Badan Pusat Statistik) in January of each year is used. This index is based on prices collected in urban areas. Although rural and urban areas as well as different commodities are likely to experience differential price changes (Thomas et al. 1999; Levinsohn et al. 2003), the province-level index is used because no other consistent price index is available for the analysis period.

[20] The predicted PCE explains 80% of the variation in the actual PCE and correctly assigns 81% and 74% of households in the first one and two quintiles within each village in the 1993 and 1994 SUSENAS. The household-level variables included in this exercise are unlikely to be changed by the program. For example, benefits were unlikely to be spent on the educational attainment of household heads who were, on average, 43 years old. Although benefits could be spent on housing improvement or to accommodate additional household members, based on the identification strategy used in Yamauchi (2008), the effects of IDT on household size and composition are insignificant, except for a decrease in the fraction of children aged 0–4. The effects on three housing quality indicators also show insignificant changes. While another housing quality indicator shows an improvement, two other indicators exhibit deteriorations, suggesting that these changes are unlikely to be due to IDT.

Second, program benefits are measured by a household's eligibility, receipt of a loan, and loan size. The 1996 and 1997 SUSENAS asked whether anyone in a household had ever been a member of a community group for IDT (members are eligible for a loan), whether that person had received an IDT loan, and if so, the year of receipt and the yearly total loan size.[21] Using the 1997 SUSENAS, I create cumulative benefit indicators such as a dummy variable indicating eligibility or a loan provided at some point between 1994 and 1996. The cumulative value of loans extended during this time period is also used. These indicators are based on retrospective information on received benefits. They are used to examine the overall allocation of benefits throughout the program period. Using the 1996 and 1997 SUSENAS, I also create yearly benefit indicators, such as a dummy variable indicating loans received and the value of those loans in a certain year. These indicators facilitate the investigation of changes in targeting performance.[22]

The yearly benefit indicators are derived from either contemporaneous or retrospective information. When contemporaneous data are used, only the information on benefits received in the year previous to the survey year is used. That is, benefits received in 1995 and 1996 are extracted only from the 1996 and 1997 SUSENAS, respectively. When retrospective information is used, benefits received in 1995 can be extracted from not only the 1996 but also the 1997 SUSENAS. Similarly, benefits received in 1994 can be extracted from these two waves of SUSENAS.[23] These two methods have different advantages. Retrospective data allow the assessment of targeting performance for a longer time period, and this accommodates a specification with fixed effects at a more disaggregated level. In contrast, contemporaneous

[21] Reported participation included a case where the household directly received loans and a case where the community group received grants and the household was a member of the group at the time of the survey. In the latter case, the grant value per group member was reported as the loan size (SUSENAS 1996, Manual IIIA). These two cases are indistinguishable. Although the data indicate that loan size does not vary among recipients in about 38% of the sample villages with more than one recipient per year, this could be the result of allocating loans of the same size. To the extent that the latter type of reporting took place when in fact relatively wealthier (poorer) households among the group kept a larger share, the targeting measures based on this information are overestimated (underestimated). The questionnaire and other documentation are available at http://www.rand.org/labor/bps.data/webdocs/susenas/susenasmain.htm.

[22] The 1998 SUSENAS also provides the information on loans received in 1996 and 1997, but since it asks the year of receipt and loan size only for the last loan received, data consistent with those based on the 1996 and 1997 SUSENAS cannot be constructed.

[23] Households in the 1996 SUSENAS report loans extended in 1994 and 1995, and those in the 1997 SUSENAS report loans extended in 1994–96. Information on the year in which a household became eligible for IDT loans is unavailable; thus, the information on eligibility is used only in the cross-sectional analysis of cumulative benefit indicators.

data provide benefit receipt information that is less likely to be subject to a possible error due to memory loss. Below I compare the results of descriptive and regression analysis based on these two types of data.

In order to measure targeting performance, I use (*a*) the degree to which relatively poor households receive benefits and (*b*) the share of benefits accruing to relatively poor households. The degree of targeting is estimated by the coefficient of the household poverty level in the regression of household-level benefits. A negative coefficient indicates a tendency to target the poor. I further investigate how the coefficient differs across villages with various initial conditions.[24] The other set of targeting measures indicates the concentration of beneficiaries and benefits among relatively poor households. These measures facilitate the decomposition analysis of distributional outcomes (Coady and Skoufias 2004; Duclos, Makdissi, and Wodon 2005).

B. Targeting: Overall, Inter-Village, and Within-Village Allocation

Overall, IDT benefits are more likely to be provided to relatively poor households. At the end of the program, the share of eligible households was 31%, and the share of households that had received a loan was 26% for the first (poorest) decile (fig. 1A). The respective figures for the 10th (richest) decile are 7% and 5%. However, among loan recipient households, the poorer received smaller loans (fig. 1B). Altogether, the distribution of the average cumulative loan size, which includes nonparticipants as zeros (or the unconditional loan size), exhibits a negative slope, suggesting that the propoor distribution of beneficiaries dominates the prorich distribution of conditional loan size. Consistently, the bottom 40% of the PCE distribution received 53% of the benefits (table 1, row C). This amounts to a 32% increase compared to its share under universal provision (40%). The equivalent figure for the distribution of beneficiaries (both in terms of eligibility and participation) is 59%, or a 48% improvement over universal provision (rows B and C). These numbers are comparable to the median achievement among programs that adopt similar targeting schemes: the figures are 40% for community-based targeting and 33% for geographic targeting (Coady et al. 2004).[25]

[24] Similar strategies are used in Jayne et al. (2001, 2002) and Alderman (2002).

[25] The performance indicator in Coady et al. (2004) should be taken as a rough measure. It is based on the share of benefits accruing to a target group. However, when this information is unavailable, the share of beneficiaries in the target group is used instead. The performance indicator also uses the bottom two quintiles as a preferred target group. However, when benefits accruing to this group are unknown, the bottom quintile is used as an alternative target group. Also, the concentration measures indicate a large variation. On the one hand, no eligibility (actual participation or loan money) was allocated to the bottom 40% of households in 8% (10%) of targeted villages. On the other hand, all

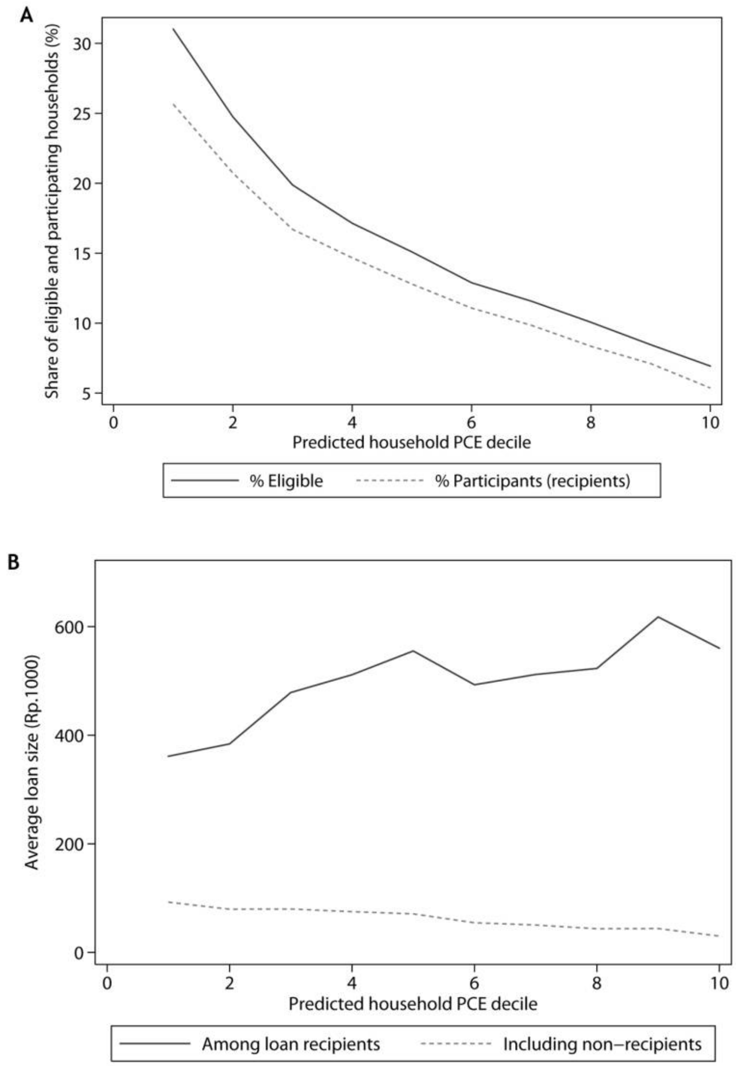

Figure 1. Distribution of overall IDT beneficiaries and benefits by decile of predicted household per capita expenditure (PCE; 1997, households in rural Indonesian villages). *A*, Share of beneficiaries. *B*, Average loan size. Sources: 1997 SUSENAS and IDT data. Households are divided into deciles based on the predicted real household per capita expenditure (PCE). See Sec. III for details of the prediction procedure. PCE and loan size are in 1995 prices. Participating households are defined as households having received at least one IDT loan. Loan size is the cumulative amount of money lent to a household over the program period. When nonrecipients are included, the loan value for them is assumed to be zero.

TABLE 1

SHARE OF CUMULATIVE IDT BENEFITS ACCRUING TO RELATIVELY POOR HOUSEHOLDS (A) IN RURAL INDONESIA AND (B) WITHIN EACH RURAL IDT VILLAGE (1994–96)

	Beneficiaries		Benefit Value	
	Bottom 20%	Bottom 40%	Bottom 20%	Bottom 40%
	A. In Rural Indonesia			
Results of across-village targeting:				
A. Beneficiaries = households in IDT village; Benefit value = per household IDT grant	28.2	49.1	27.4	48.8
Results of across-village and within-village targeting:				
B. Beneficiaries = eligible households	35.3	58.8		
C. Beneficiaries = households receiving a loan; Benefit value = loan value	35.1	58.8	27.7	52.7
	B. Within Each Rural IDT Village			
Results of within-village targeting:				
D. Beneficiaries = eligible households	23.5	44.7		
E. Beneficiaries = households receiving a loan; Benefit value = loan value	23.8	44.8	23.4	44.6
Results of counterfactual allocation:				
F. Beneficiaries = households where the head did not complete primary school	25.0	46.4		
G. Beneficiaries = households living in a house where floor is made of earth	28.9	49.4		
Results of within-village yearly tageting based on retrospective data:				
H. Beneficiaries = households receiving a loan in 1994; Benefit value = 1994 loan value	25.6	46.2	25.6	46.0
I. Beneficiaries = households receiving a loan in 1995; Benefit value = 1995 loan value	23.6	44.0	23.5	43.9
J. Beneficiaries = households receiving a loan in 1996; Benefit value = 1996 loan value	22.4	43.5	22.1	43.4
Results of within-village yearly targeting based on contemporaneous data:				
K. Beneficiaries = households receiving a loan in 1995; Benefit value = 1995 loan value	23.8	44.2	23.8	43.9
L. Beneficiaries = households receiving a loan in 1996; Benefit value = 1996 loan value	22.4	43.5	22.0	43.4

Sources. 1997 SUSENAS and IDT data.

Note. Overall beneficiaries are defined as either eligible households or households receiving at least one loan by January of 1997. Potential beneficiaries (which reflect only the result of village selection, and not the result of within-village selection of households) are defined as households residing in villages funded at least once under IDT. Overall benefits are defined as the cumulative loan value. Potential benefits (which reflect only the result of grant allocation across villages, and not across households within a village) are defined as per household cumulative IDT grant value. Funded villages received Rp. 20 million per annum. The number of households as of 1993, prior to the start of IDT, is used. For rows A, B, and C, relatively poor households are defined as those with predicted household per capita expenditure (PCE) falling in the bottom 20% or 40% of the distribution *for rural Indonesia as a whole*. For rows D through L, relatively poor households are defined as those with predicted per capita expenditure (PCE) falling in the bottom 20% or 40% of the distribution *for each rural IDT village*. Rows D and E indicate the results of actual benefit allocation throughout the program period, while rows F and G show the results of counterfactual allocation based on the rule of extending a loan to either a household headed by a person without primary school education or a household living in a house where the floor is made of earth. Rows H, I, and J indicate yearly, instead of cumulative, benefit allocation. Rows K and L also depict yearly benefit allocation. Unlike the results in other rows (which are based on retrospective information in the 1997 SUSENAS), the results in these rows are based on the contemporaneous benefit receipt information. That is, information for 1995 is extracted from the 1996 SUSENAS, and information for 1996 is from the 1997 SUSENAS. See Sec. III.A for more details.

The overall distribution of IDT benefits can be decomposed into an inter-village and within-village allocation. In order to do this, I define households in villages that have been funded at least once to be potential beneficiaries. Similarly, I define per household grant value (the total grant value divided by the 1993 number of households in the village) as the potential benefit value. While the distribution of actual beneficiaries/benefits indicates the result of both inter-village and intra-village selection, the distribution of potential beneficiaries/benefits reflects only the result of inter-village selection. According to these potential benefit indicators, inter-village allocation explains a large part of overall targeting. The bottom 40% of the PCE distribution had 49% of beneficiaries and benefits (table 1, row A).[26] However, the share achieved by the overall targeting exceeds these figures (rows B and C), suggesting the contribution from within-village targeting. It particularly contributes to overall targeting in terms of beneficiaries. The share of beneficiaries belonging to the bottom 40% increases by 10 percentage points, though this improvement is offset by 6 percentage points by the prorich distribution of loan size among beneficiaries.

The analysis so far has not taken into account the fact that households from one village could all be included in one decile. In order to focus on within-village targeting, the exercise is repeated using the predicted PCE that is standardized within each village. Both the nonparametric and linear relationships demonstrate that the probability of participating in IDT increases by 6 percentage points as a household's predicted PCE decreases by one standard deviation (fig. 2A).[27] On the other hand, cumulative loan size does not vary much within a funded village (fig. 2B). This suggests that the prorich distribution of conditional loan size (fig. 1) is due to larger loans provided in wealthier IDT villages. With no within-village variation in conditional loan size, the distribution of unconditional loan size reflects the propoor distribution of participants. Also, the share of beneficiaries and benefits accruing to the bottom 40% coincide at 45% (table 1, rows D and E). These results confirm that there is a contribution of community-based targeting toward overall targeting and that most of the contribution arises from the selection of beneficiaries. The results are comparable to a counterfactual targeting outcome

eligibility (participation or loan money) was allocated to the bottom 40% in 7% (8%) of the villages. Distributions better than universal allocation are found in 40% (43%) of villages in terms of eligibility (participation or loan money). This concentration of extreme mistargeting is analogous to the high concentration of the incidence of missing rice under Indonesia's OPK program (Olken 2006).

[26] The share does not vary by the choice of benefit measure (beneficiaries and benefit value). That is, conditional on grant receipt, the per household grant value does not vary across deciles. This is consistent with the fact that village size is not highly correlated with the PCE level.

[27] The relationships for the probability of being eligible indicate a very similar pattern. The similarity between linear and nonlinear estimation also suggests that the linear specification used in the following analysis is a reasonable approximation.

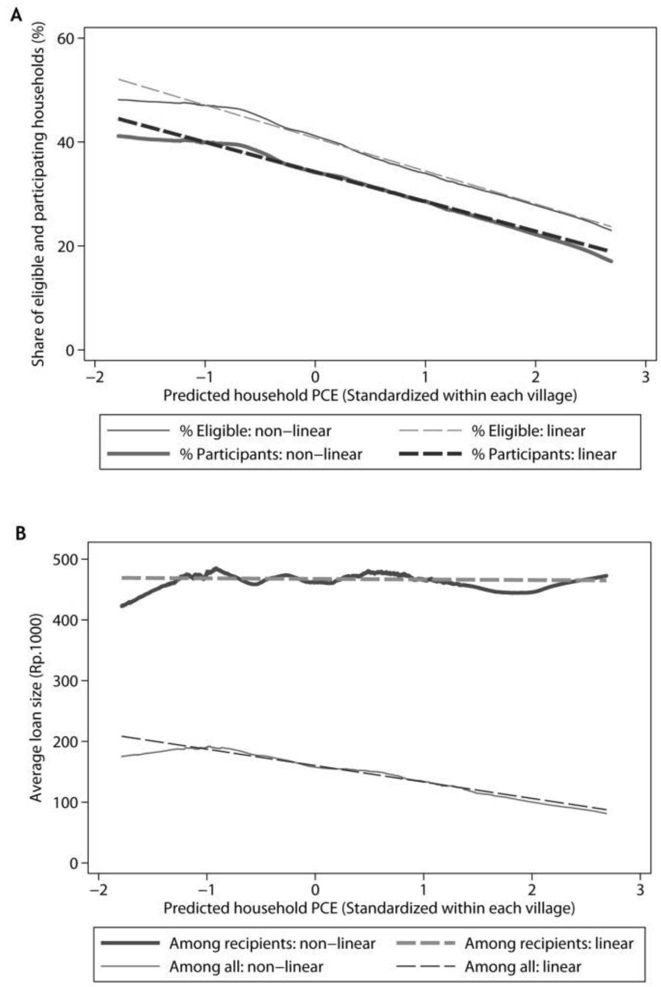

Figure 2. Within-village distribution of IDT beneficiaries and benefits by quintile of standardized predicted household PCE (1996 and 1997, households in rural Indonesian villages funded at least once under IDT). *A*, Share of beneficiaries. *B*, Average loan size. Sources: 1997 SUSENAS and IDT data. Part *A* depicts the nonparametric relationship between the share in targeted villages of eligible households (which have become eligible for an IDT loan by 1997) and the predicted, standardized household PCE. It also indicates the relationship between the share of participating households (that have ever received an IDT loan by 1997) and the predicted standardized household PCE. The nonparametric estimation is based on STATA's lowess procedure. The straight lines indicate the OLS fitted values. Part *B* shows linear and nonparametric relationships between the predicted standardized household PCE and the average loan value received under IDT with and without including nonparticipants as zeros. See the note for fig. 1 for the definitions of participation and loan size, and see Sec. III for details of the procedure for predicting household PCE.

where loans were provided to all households where the head did not complete primary school (row F), and they are slightly worse than another counterfactual case where loans were given to households living in a house where the floor was made of earth (row G).

However, once benefits are broken down by the year of receipt, it is revealed that targeting deteriorated over time. The results based on retrospective information suggest that the deterioration is particularly severe for the poorest quintile, where the share of benefits declined by 3 percentage points (13% of its 1994 share, rows H, I, and J) between 1994 and 1996. The results based on contemporaneous data suggest a consistent deterioration in targeting (rows K and L). Between 1995 and 1996, the share of benefits declined by about 1.4–1.8 percentage points for the bottom quintile.

IV. Empirical Strategy

Village conditions associated with these targeting outcomes are investigated in two steps. First, I explore which village characteristics are correlated with overall targeting performance, measured by the allocation of *cumulative* benefit. Next, I investigate which characteristics are associated with changes in targeting performance, using *yearly* benefit allocation.

A. Overall Benefits

In order to analyze the overall benefit allocation, two specifications are used that extend the descriptive analysis based on the coverage of relatively poor households and the concentration of program resources. The first specification is the following household-level regression model with the village-level fixed effects:

$$Y_{ij} = \alpha_0^H + \beta_0^H X_{ij} + \beta_1^H (X_{ij} \times V_j) + \beta_2^H (X_{ij} \times D_j) + \mu_j^H + \epsilon_{ij}^H. \quad (1)$$

The outcome variable, Y_{ij}, denotes overall benefits received between 1994 and 1996 by a household i in village j. Parameter β_0^H indicates the baseline degree of targeting, or the correlation between the outcome and the household's relative poverty level within the village, X_{ij}, measured by the standardized, predicted PCE. Parameter β_1^H allows the degree of targeting to differ across villages depending on their preprogram characteristics, V_j. With the village-level fixed effects, μ_j^H, these parameters estimate the correlation net of possible across-village additive differences in the level of benefits. For example, village fixed effects absorb differences in the participation rate common within a village for relatively poor and wealthy households, which might arise from the heterogeneous preference of village officials over wide coverage versus large benefit per recipient. In addition, it is possible that the selection of poor villages is correlated with unobserved factors that affect targeting (Galasso and Ravallion 2005). This is controlled for by a set of variables characterizing the selection process, D_j, interacted with the household's relative poverty level.[28] The error term, ϵ_{ij}^{H}, is assumed to be independent across villages.

The second specification is the following village-level model with the subdistrict-level fixed effects:

$$Y_{jk} = \alpha_0^V + \beta_1^V V_{jk} + \beta_2^V D_{jk} + \mu_k^V + \epsilon_{jk}^V. \tag{2}$$

The outcome variable is the share in village j in subdistrict k of overall benefits (cumulative loan value) or beneficiaries (defined by eligibility or participation) accruing to relatively poor households, with predicted PCE falling in the bottom 20% or 40%. The parameter of interest, β_1^V, indicates the correlation between these concentration measures and preexisting village conditions. Similar to equation (1), the village selection process is controlled for by including D_{jk}. Note that, under specifications (1) and (2), different changes in benefit allocation are considered as targeting neutral. While equation (1) takes a constant additive change as neutral, equation (2) takes a proportional change as neutral (see appendix B.1). The following analysis focuses on village characteristics that are consistently related to targeting performance under the two specifications.

B. Initial Local Conditions and Targeting

Possible pathways through which different initial local conditions affect community-based targeting can be illustrated in the village-level welfare maximization framework. Suppose that village officials try to maximize the weighted welfare of relatively poor and wealthy households. For simplicity, I call them the poor and the nonpoor.[29] First, the effect of inequality is unclear. On the

[28] The set of variables characterizing the selection process, D_j, includes the 1994 and 1995 differences between the village score and the provincial threshold, which represent the propensity to be funded in the respective years. It also includes a dummy variable that indicates a village where funding status in 1994 depended on a field officer's subjective evaluation. Two additional dummy variables are included to indicate villages selected for funding in later years based on the 1995 and 1996 criteria. Another dummy variable indicates villages that were once funded but that dropped out of the funding list in 1995 or 1996. Finally, the last dummy variable indicates villages funded in 1994 or 1995 despite the village selection rules suggesting no funding. Other types of errors are too rare to be included.

[29] The discussion in this section follows the model used in Galasso and Ravallion (2005). The village welfare function can be denoted as $W = 1/2[\lambda_P(Y_P, V)W_P(Y_P, V)] + 1/2[\lambda_N(Y_N, V)W_N(Y_N, V)]$, where λ_P and λ_N are the weights for a relatively poor half and a relatively wealthy half of the households in a village, V is village characteristics that affect the aggregate welfare level and the weight for the relatively poor and the relatively nonpoor, and Y_P and Y_N are per capita benefit among the poor and nonpoor, respectively. Under the budget constraint of $1/2(Y_P) + 1/2(Y_N) = G$, where G is the per household grant value, the optimal allocation equates $(\partial\lambda_P/\partial Y_P)W_P + \lambda_P(\partial W_P/\partial Y_P)$ (the marginal gain in village welfare from increasing Y_P) and $(\partial\lambda_N/\partial Y_N)W_N + \lambda_N(\partial W_N/\partial Y_N)$ (the marginal loss in village welfare from

one hand, inequality can increase the gap in the marginal welfare levels between the poor and the nonpoor from receiving an IDT loan, providing officials with an incentive to concentrate program resources to the poor. On the other hand, inequality may tilt the weights on the welfare functions in favor of the nonpoor. Over time, the relative importance of these factors could change. For example, if benefits provided to the poor empower them, the weight on the welfare of the poor could increase. This issue is explored using two indicators of inequality in consumption and education levels: the coefficient of variation of the predicted PCE[30] and an education Gini index.[31]

Second, the human capital of village heads and the administrative capability of village government can enhance better targeting if they are correlated with relatively equal weights on the welfare functions of the poor and nonpoor and if there is more accurate information on the marginal welfare obtained from receiving an IDT loan. The human capital of village heads is measured by their educational attainment conditional on their cohort,[32] and the technical competency of village government, LKMD, is measured by its self-reported capacity.[33] Measures are also included for the preexistence of social organizations such as groups of farmers, health/nutrition advisors, and agricultural extension workers.

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increasing Y_P).

[30] The inequality measure and the average poverty level are based on the predicted PCE of surveyed households, which are not representative at the village level. Possible measurement errors in these variables could create an attenuation bias. Thus, the magnitude of the estimates is likely to be interpreted as the lower bound. This is true for the share of household heads who completed primary education and the education Gini index. All the other village characteristics are based on village-level census data: the 1993 PODES and IDT administrative data.

[31] To measure inequality in educational attainment, I follow Thomas, Wang, and Fan (2001) using six educational attainment categories: none, some primary education, completed primary education, junior secondary education, senior secondary education, and higher education. (See appendix table A3 for the summary statistics of village characteristics.)

[32] Younger village heads are more likely to have completed higher levels of education. In order to separate the cohort effect from the education effect, I define relatively educated village heads by age group. Thus, the interaction between age dummies and education dummy indicates, given the village head's age group, whether the head's exposure to relatively higher education is associated with targeting performance.

[33] LKMD is the national institution operating at the village level. It was created in the beginning of the 1980s as a vehicle to implement national programs for villages. Its members are usually local residents, appointed by the village head (Antlov 2003). The PODES asks whether the LKMD in each village (i) does not exist, (ii) only exists in very basic form, (ii) exists and is able to develop and conduct work projects utilizing grants from the central government matched with contributions of community members, or (iv) exists and forms village development plans, keeps reports in order, and has well-functioning sections. In order to reduce the effect of subjective evaluation, I define a village in iii or iv as a village with relative technical competence. Since the form of LKMD was originally developed in Java and was later put in place in other regions, I allow the correlation with targeting performance to vary inside and outside of Java.

Third, the marginal welfare from receiving IDT loans is likely to be higher if returns to investment are higher and the preexisting supply of credit is scarce. These conditions may also reduce the gap in the marginal welfare levels among the poor and nonpoor. This possibility is tested using the dummy variables indicating villages with and without three types of credit institutions: banks, cooperatives, and past public credit programs. Dummies are also included indicating local investment environments such as having no land access to outside the village, road conditions among villages with land access, and access to public transportation and communication facilities.

Fourth, a smaller budget size can hinder targeting if allocation to the nonpoor is prioritized. Under IDT, per capita grant size varied across villages because the same value of lump sum grant was given to all selected villages regardless of population size. The correlation between the per capita grant size and targeting performance cannot, however, be separated from a possible association between population size and targeting performance.[34] Thus, the overall correlation between population size and targeting performance is investigated, controlling for different funding history.[35]

V. Results on Overall Targeting Performance

On average, within-village targeting was propoor. The average degree of targeting indicates that, for the average village, a one standard deviation increase in household predicted PCE decreases the probability of eligibility (participation) by 6.4 (5.8) percentage points (table 2).[36] It also decreases loan size by Rp. 27,581. These figures are equivalent to 16%–17% of the respective averages (appendix table A1). Altogether, the results are consistent with the findings in figure 2 and table 1.[37]

Among the list of village characteristics, the major correlates of better

[34] However, the magnitude of the correlation between population and village institutions affecting targeting is likely, if anything, to be weak in Indonesia. This is because villages with a growing population were often split to maintain a certain village size. For example, population size is not highly correlated with the average village PCE.

[35] I also include two dummy variables indicating villages that recently experienced negative income shocks, such as natural disasters and epidemics, to see whether they show poorer targeting due to the need to assist wealthier households in transient poverty. Information on religion and ethnicity is unavailable.

[36] Average degree of targeting is computed as $\beta_0^H + (\beta_1^H \times \bar{V}) + (\beta_2^H \times \bar{D})$ (shown in the first row in table 2), based on the estimates for β_0^H, β_1^H, and β_2^H (in the rest of the rows) in eq. (1), where $\bar{V}$ and $\bar{D}$ are the mean characteristics of the sample villages observed in the 1997 SUSENAS.

[37] When household characteristics are used instead of the relative poverty level, the results show that households are more likely to receive loans if they have less educated male heads, many more members, a higher share of women and children, and housing made of inferior materials. Larger households headed by males are more likely to receive larger loans among recipients (appendix table A5).

TABLE 2

HETEROGENEITY BY VILLAGE CHARACTERISTICS IN THE RELATIONSHIP BETWEEN PREDICTED HOUSEHOLD PCE AND IDT ELIGIBILITY, PARTICIPATION, AND LOAN SIZE (1997, RURAL INDONESIA); UNIT OF OBSERVATION = HOUSEHOLD; VILLAGE-LEVEL FIXED EFFECTS MODEL

	Eligibility (1)	Participation (2)	Participation Given Eligibility (3)	ln(Loan Size Given Participation) (4)	Loan Size Including Zeros (5)
Average degree of targeting	−.064	−.058	−.009	−.007	−27.581
P-value	.000	.000	.004	.400	.000
Selected estimates for eq. (1):					
Predicted standardized household PCE	−.064*	−.059*	.003	−.037	−3.647
	(.016)	(.016)	(.017)	(.054)	(19.905)
The interaction between the predicted household PCE and:					
Village-level average predicted PCE (1995 Jakarta prices, standardized)	−.011*	−.009*	−.002	.001	−7.037^{+}
	(.003)	(.003)	(.003)	(.010)	(3.448)
Village-level coefficient of variation in the predicted PCE (standardized)	−.016*	−.015*	−.003	−.015	−7.413*
	(.002)	(.002)	(.003)	(.009)	(2.227)
Population (1,000 persons)	.008*	.007*	.000	.009	4.911*
	(.001)	(.001)	(.002)	(.006)	(.943)
Density (100 persons per hectare)	−.056	−.079	−.154^{+}	.280	−6.383
	(.042)	(.043)	(.078)	(.185)	(22.964)
Share of household heads in the village who completed primary education or above	−.017	−.011	−.006	−.003	−10.941
	(.011)	(.011)	(.011)	(.034)	(13.935)
Village-level education Gini index	−.007	.003	.005	.000	−30.004^{+}
	(.013)	(.013)	(.012)	(.039)	(13.658)
Village head is aged 39 or less	.011	.011	.007	.017	−5.889
	(.007)	(.007)	(.008)	(.032)	(9.686)
Village head is aged 39 or less and completed high school or higher education	−.018^{+}	−.013	.003	.010	4.388
	(.007)	(.007)	(.007)	(.026)	(9.963)
Village head is aged 40–47	−.002	.004	.011	.037	6.397
	(.007)	(.007)	(.007)	(.030)	(8.928)
Village head is aged 40–47 and completed junior high school or higher education	−.005	−.003	−.001	−.024	−8.665
	(.007)	(.007)	(.007)	(.022)	(7.928)
Village head is aged 48 and above and completed junior high school or higher education	−.008	−.007	−.004	.022	−7.205
	(.007)	(.007)	(.008)	(.030)	(8.630)
Village head is female	−.005	.001	−.004	.028	−.239
	(.018)	(.017)	(.011)	(.033)	(8.649)

Village government (LKMD) is established × outside of Java	−.004	−.005	−.002	−.014	−16.138^{+}
	(.005)	(.005)	(.006)	(.022)	(7.823)
Village government (LKMD) is established × Java	−.013	−.017	−.020	.072	2.733
	(.012)	(.011)	(.014)	(.059)	(18.062)
Village has farmers' associations	−.001	−.004	−.009	−.017	−.815
	(.005)	(.005)	(.005)	(.020)	(6.061)
Village has groups of advisors such as agricultural extension and health and nutrition	.004	.003	−.003	.030	5.089
	(.005)	(.005)	(.004)	(.020)	(6.559)
Village has at least one cooperative	.005	.002	−.008	−.017	−2.042
	(.005)	(.005)	(.008)	(.020)	(5.894)
Village has at least one bank	−.012	−.007	.012	−.007	2.731
	(.006)	(.006)	(.009)	(.025)	(5.856)
Village received at least one credit program in the previous year	−.015*	−.012*	.010	.010	−2.485
	(.005)	(.005)	(.006)	(.016)	(5.996)
Village's main access is through land	−.004	−.003	.003	−.025	−16.062
	(.007)	(.007)	(.007)	(.033)	(11.775)
Village's main access is through land and the inter-village road is made of asphalt or hardened	.006	.004	−.007	.016	12.637^{+}
	(.005)	(.005)	(.006)	(.014)	(5.709)
Village has access to public transportation within the village	.001	.004	.006	−.010	5.341
	(.004)	(.004)	(.005)	(.019)	(5.311)
Village has a public television	.000	−.004	−.008	.041	4.982
	(.005)	(.005)	(.006)	(.024)	(5.973)
Village has a post office	.002	−.004	−.020	−.024	−8.044
	(.008)	(.008)	(.017)	(.030)	(5.553)
Village experienced natural disasters such as droughts, floods, earthquakes, and volcano eruptions at least once in the past 3 years	−.002	−.004	−.008	.013	5.643
	(.004)	(.004)	(.005)	(.016)	(5.622)
Village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year	−.005	.000	.011	−.026	−4.611
	(.005)	(.005)	(.006)	(.019)	(6.365)
Village's grant status in 1993 depends on field officers' subjective perceptions	−.011	−.009	.000	.034	.713
	(.007)	(.006)	(.007)	(.024)	(9.436)
Village is newly added to the treatment group in 1995	−.008	.003	.003	.033	21.254
	(.010)	(.009)	(.010)	(.040)	(15.319)
Village is newly added to the treatment group in 1996	.018	.027*	.000	.032	21.226
	(.010)	(.010)	(.013)	(.047)	(14.524)
Village was once funded but dropped out of the treatment group in 1995 or 96	.019	.016	.003	−.021	−20.632
	(.010)	(.011)	(.007)	(.020)	(16.602)

TABLE 2 (*Continued*)

	Eligibility (1)	Participation (2)	Participation Given Eligibility (3)	ln(Loan Size Given Participation) (4)	Loan Size Including Zeros (5)
Difference between the village score and the 1993 provincial threshold	.006	.003	−.002	−.021	1.416
	(.003)	(.003)	(.004)	(.020)	(3.304)
Difference between the village score and the 1994 provincial threshold	−.001	.003	.005	.015	−.914
	(.002)	(.002)	(.003)	(.010)	(2.521)
Village was funded in 1993 or 1994 despite the rules suggesting no funding	.010	.000	−.023	−.010	−23.530
	(.019)	(.017)	(.018)	(.061)	(21.763)
Sumatera	.016	−.002	−.008	−.017	−16.531
	(.009)	(.009)	(.009)	(.026)	(10.975)
Java	.029+	.014	.004	−.153+	−12.811
	(.015)	(.014)	(.019)	(.073)	(20.015)
Nusa Tenggera	−.007	−.011	−.009	−.012	−4.655
	(.010)	(.009)	(.010)	(.025)	(8.425)
Kalimantan	.015	.003	−.008	−.127	−52.738*
	(.010)	(.010)	(.013)	(.072)	(17.051)
Sulawesi	−.003	−.014	.005	−.022	−11.709
	(.011)	(.010)	(.011)	(.030)	(9.982)
Constant	.408*	.343*	.839*	12.267*	160.217*
	(.000)	(.000)	(.000)	(.001)	(.000)
No. of observations	46,836	46,836	19,091	16,048	46,836
Villages	2,832	2,832	2,382	2,241	2,832
F-statistic	28.19	24.65	.98	.93	5.45

Sources. 1997 SUSENAS, 1993 PODES, and IDT data.

Note. Selected estimates for eq. (1) are shown together with the average degree of targeting and the *p*-value for the test of whether the average degree of targeting is zero. See n. 36 for the computation of the average degree of targeting. All the regression equations include five dummy variables indicating regions (Sumatera, Java, Nusa Tenggera, Kalimantan, and Sulawesi). All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. Predicted household PCE is based on the preprogram relationship between household PCE and characteristics (appendix table 2). The predicted value is standardized within the village to focus on the relative poverty level of households within the village. Column 4 shows the regression of the natural logarithm of loan size only for recipients. Column 5 shows the regression of unconditional loan size that includes nonrecipients as zeros. The results based on nonlinear specifications provide substantively consistent findings. See n. 44 for details. Standard errors are in parentheses.

+ Significant at the 10% level.

* Significant at the 5% level.

targeting are the average level of predicted PCE and its inequality. First, as the average PCE increases by one standard deviation (Rp. 8,938), a marginally poorer household is 1 percentage point more likely to be both eligible and participating. The household also receives Rp. 7,037 larger benefits unconditional on loan receipt (table 2). These changes amount to 16%–26% of the average degree of targeting. Consistently, a one standard deviation decrease in the average PCE is associated with a decline of 4−5 percentage points (11%–20% of the respective average share) in the share of benefits accruing to relatively poor households (table 3). One reason for these results may be that all households are considered deserving in poorer villages. Nine percent of the relatively poor half of the villages had all households eligible, and 6% had all households receiving a loan. The equivalent figures are 4% and 3% among the relatively wealthy half of the villages. These results could also reflect unobserved local institutions common in wealthier villages, which enable more transparent and propoor resource allocation.

Second, a one standard deviation increase in the coefficient of variation in the predicted PCE is accompanied by a 2 percentage point improvement in the degree of targeting in terms of eligibility and participation and a Rp. 7,413 increase in the unconditional loan value. This is equivalent to a 25%–27% improvement relative to the average degree of targeting (table 2). Interestingly, the results in table 3 suggest that it is households in the second, and not the first, quintile who benefited the most from greater inequality. A one standard deviation increase in the inequality measure is associated with a 0.2 percentage point larger share of participants for the poorest group (1% of the average share). This is positive, yet only a fifth of the 5% increase (2 percentage points) for the bottom two quintiles. These results suggest that inequality in the living standard may help village officials to differentiate households in the second poorest quintile from households in the third quintile or above—this could be more difficult in more equal villages.[38] On the other hand, the poorest group is more likely to be included among the beneficiaries regardless of the level of within-village inequality. Although information on wealth inequality is unavailable in the SUSENAS, the results on inequality in educational attainment suggest a weak, but similar, tendency: unequal villages exhibit better targeting of households in terms of unconditional loan size (table 2). Altogether, these results suggest that ease of identifying the poor and of justifying their needs could possibly overwhelm the larger political influence of local elites, which might be greater in more unequal

[38] For example, if households with a similar poverty level were clustered in the second and third quintiles within a village, their relative poverty status might not have been accurately distinguished.

TABLE 3

VILLAGE CHARACTERISTICS ASSOCIATED WITH THE SHARES OF OVERALL BENEFICIARIES AND BENEFITS FOUND IN THE BOTTOM TWO AND FOUR QUINTILES OF PREDICTED HOUSEHOLD PCE (1997, RURAL INDONESIA), UNIT OF OBSERVATION = VILLAGE; SUBDISTRICT-LEVEL FIXED EFFECTS MODEL

	Share of Eligible Households Whose PCE Is Below:		Share of Participating Households Whose PCE Is Below:		Share of Loan Money Share of Loan Money Households Whose PCE Is Below	
	20th Percentile (1)	40th Percentile (2)	20th Percentile (3)	40th Percentile (4)	20th Percentile (5)	40th Percentile (6)
Village-level average predicted PCE (1995 Jakarta prices, standardized)	.047*	.049*	.044*	.043+	.046*	.048*
	(.011)	(.014)	(.014)	(.017)	(.015)	(.018)
Village-level coefficient of variation in the predicted PCE (standardized)	.006	.026*	.002	.021+	.005	.018
	(.007)	(.008)	(.008)	(.010)	(.008)	(.010)
Population (1,000 persons)	−.003	−.005	.004	.000	.003	.000
	(.005)	(.006)	(.006)	(.007)	(.006)	(.008)
Density (100 persons per hectare)	−.166	.117	−.270	.047	−.061	.129
	(.231)	(.275)	(.268)	(.333)	(.286)	(.350)
Share of household heads in the village who completed primary education or above	−.069	−.017	−.075	.044	−.088	−.007
	(.039)	(.046)	(.045)	(.056)	(.048)	(.059)
Village-level education Gini index	.027	.099	.053	.106	.069	.090
	(.044)	(.052)	(.051)	(.064)	(.055)	(.067)
Village head is aged 39 or less	−.035	−.024	−.037	−.040	−.034	−.043
	(.018)	(.022)	(.021)	(.027)	(.023)	(.028)
Village head is aged 39 or less and completed high school or higher education	.030	.014	.016	.019	.019	.027
	(.022)	(.026)	(.025)	(.031)	(.027)	(.033)
Village head is aged 40–47	−.024	.006	−.017	.001	−.027	−.020
	(.018)	(.021)	(.021)	(.026)	(.022)	(.027)
Village head is aged 40–47 and completed junior high school or higher education	.014	.014	.005	−.001	.027	.023
	(.020)	(.024)	(.023)	(.029)	(.025)	(.031)
Village head is aged 48 and above and completed junior high school or higher education	−.026	.001	−.036	−.017	−.025	−.013
	(.020)	(.024)	(.023)	(.029)	(.025)	(.031)

Village head is female	−.060	−.001	−.093	−.012	−.103	−.007
	(.043)	(.051)	(.051)	(.063)	(.054)	(.066)
Village government (LKMD) is established} × outside of Java	.013	−.020	.005	.004	.021	.001
	(.018)	(.021)	(.021)	(.026)	(.022)	(.027)
Village government (LKMD) is established} × Java	−.089	−.076	.015	−.113	.030	−.068
	(.174)	(.208)	(.192)	(.238)	(.205)	(.250)
Village has farmers' associations	.001	.017	.011	.022	.004	.021
	(.015)	(.018)	(.017)	(.021)	(.018)	(.022)
Village has groups of advisors such as agricultural extension and health and nutrition	−.009	−.022	−.028	−.022	−.018	−.027
	(.016)	(.019)	(.018)	(.023)	(.019)	(.024)
Village has at least one cooperative	−.001	.004	−.003	−.008	−.001	.002
	(.016)	(.019)	(.019)	(.023)	(.020)	(.025)
Village has at least one bank	.002	−.036	.001	−.050	−.006	−.060
	(.023)	(.028)	(.028)	(.034)	(.029)	(.036)
Village received at least one credit program in the previous year	.023	.020	−.001	−.020	−.003	−.019
	(.017)	(.021)	(.020)	(.025)	(.022)	(.026)
Village's main access is through land	.024	−.025	.028	.002	.064	.028
	(.028)	(.033)	(.033)	(.041)	(.036)	(.043)
Village's main access is through land and the inter-village road is made of asphalt or hardened	−.016	−.020	−.032	−.025	−.036+	−.032
	(.015)	(.018)	(.017)	(.021)	(.018)	(.022)
Village has access to public transportation within the village	−.008	.002	−.032	−.024	−.025	−.022
	(.016)	(.019)	(.019)	(.023)	(.020)	(.024)
Village has a public television	−.009	.005	−.026	−.014	−.035	−.030
	(.015)	(.017)	(.017)	(.021)	(.018)	(.022)
Village has a post office	.011	.064+	.050	.082+	.045	.089+
	(.025)	(.030)	(.031)	(.038)	(.033)	(.040)
Village experienced natural disasters such as droughts, floods, earthquakes, and volcano eruptions at least once in the past 3 years	.033+	.011	.072*	.042	.075*	.039
	(.016)	(.019)	(.019)	(.023)	(.020)	(.025)
Village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year	.018	.020	−.001	.000	.001	.003
	(.016)	(.019)	(.018)	(.023)	(.020)	(.024)
Village's grant status in 1993 depends on field officers' subjective perceptions	−.019	.031	−.036	.007	−.028	.023
	(.020)	(.024)	(.023)	(.028)	(.024)	(.030)
Village is newly added to the treatment group in 1995	−.026	.025	−.045	.007	−.026	.035
	(.030)	(.035)	(.034)	(.042)	(.036)	(.044)

TABLE 3 (*Continued*)

	Share of Eligible Households Whose PCE Is Below:		Share of Participating Households Whose PCE Is Below:		Share of Loan Money Share of Loan Money Households Whose PCE Is Below	
	20th Percentile (1)	40th Percentile (2)	20th Percentile (3)	40th Percentile (4)	20th Percentile (5)	40th Percentile (6)
Village is newly added to the treatment group in 1996	−.006	.034	−.044	.004	−.023	.041
	(.029)	(.034)	(.033)	(.041)	(.035)	(.043)
Village was once funded, but dropped out of the treatment group in 1995 or 1996	−.028	−.004	−.022	.009	−.022	.006
	(.031)	(.037)	(.036)	(.045)	(.038)	(.047)
Difference between the village score and the 1993 provincial threshold	.007	.014	.018	.024	.017	.017
	(.011)	(.013)	(.013)	(.016)	(.014)	(.017)
Difference between the village score and the 1994 provincial threshold	.010	.007	.009	.002	.006	.002
	(.010)	(.012)	(.012)	(.015)	(.013)	(.015)
Village was funded in 1993 or 1994 despite the rules suggesting no funding	−.038	−.028	−.044	−.046	−.024	−.016
	(.058)	(.069)	(.068)	(.085)	(.073)	(.089)
Constant	.288*	.448*	.292*	.444*	.23*	.427*
	(.063)	(.075)	(.073)	(.090)	(.078)	(.095)
No. of observations	2,382	2,382	2,241	2,241	2,241	2,241
F-statistic	1.59	2.18	1.77	1.39	1.79	1.34
F(Prov FE)	1.44	1.35	1.37	1.15	1.32	1.17

Sources. 1997 SUSENAS, 1993 PODES, and IDT data.

Note. The results of estimating eq. (2) are shown. See the note for appendix table A1 for definitions of the outcome and explanatory variables. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. The number of villages is smaller than that in table 2 because villages with at least one beneficiary are used in the village-level analysis. Standard errors are in parentheses.

$^{+}$ Significant at the 10% level.

* Significant at the 5% level.

communities.[39] These findings on the levels of poverty and inequality are consistent with the cross-country study by Coady et al. (2004).[40]

These results, which are not in line with previous anecdotal evidence,[41] might reflect Indonesia's political context. In the Suharto regime, village heads had incentives to look to upper-level government, in particular, to district and subdistrict government. This is because village heads needed district-level government approval to run for village election, and they were held accountable to the subdistrict government once elected. Properly executing national programs was one way to show their capability and their loyalty to the members of these levels of government (Husken 1994; Antlov 1995). For example, Antlov (1995) reports that a village leader tried to increase participation in a literacy program to make himself look competent to subdistrict officials. Under IDT, the list of participants was reported to the subdistrict government, which provided the information to the district government. The information was in turn submitted to the provincial and central government. Village heads might have used this list to demonstrate their achievement in following the national guideline to target the poor.

The other major concern about the effectiveness of community-based targeting lies in the capability of local agents who are responsible for the allocation of program resources. However, only the results of the household-level analysis suggest that, outside Java, the level of self-reported administrative capacity of village government is correlated with better targeting in terms of unconditional loan size (table 2). Also, no clear performance gap is found among villages headed by persons with different age and education levels.[42] The other village characteristics show an association with targeting performance based on only one of the two specifications, most likely reflecting the methodological differences (see appendix B).[43] These results imply that the levels of poverty and

[39] These results also provide an indication that consideration of profitability is unlikely to be a major cause of poor targeting. For, if this were the case, inequality in education, which could be correlated with inequality in creditworthiness and entrepreneurship, should be associated with poorer targeting.
[40] Similar results are obtained when an alternative inequality measure, the Gini coefficient, is used, though no association is found when the share of the top 20% of the predicted PCE distribution is used. The positive correlation between targeting and inequality is in contrast with the results of Galasso and Ravallion (2005), who find a negative association between targeting and inequality in landholding. However, Galasso and Ravallion's definition of the poor (based on the national poverty level) makes it difficult to directly compare the two sets of results.
[41] See n. 2.
[42] Although the results of the household-level analysis indicate a significant gap among the younger cohort of village heads between the educated and the less educated, neither exhibits a significant difference compared to the omitted group of village heads—those aged 48 and above who have not completed junior high school (table 2).
[43] Proximity to the regional center is not included in the regressions as it shows few significant effects and no systematic pattern across regions. The exclusion of these factors does not alter the qualitative results.

inequality are the two major correlates of overall targeting performance. Also, the magnitude of the correlation between these two village characteristics and targeting performance is not much altered by the inclusion of the other village attributes in the regressions (appendix table A6).[44]

VI. Changes in Targeting Performance

A. Yearly Benefits

Thus far, the analysis has focused on the allocation of overall benefits received throughout the program period. This section investigates changes in targeting performance using the yearly benefit distribution. A basic household-level specification can be modified as follows:

$$\begin{aligned} Y_{ijt} = {} & \alpha_{94}^{H} + \beta_{94}^{H} X_{ijt} + \gamma_{94}^{H}(X_{ijt} \times V_j) + \delta_{94}^{H}(X_{ijt} \times D_j) \\ & + \sum_{s=95}^{96} [\alpha_s^H T_s + \beta_s^H (X_{ijt} \times T_s) + \gamma_s^H (X_{ijt} \times V_j \times T_s) \\ & + \delta_s^H (X_{ijt} \times D_j \times T_s)] + \mu_j^H + \epsilon_{ijt}^H. \end{aligned} \tag{3}$$

Parameters β_s^H show whether there are common yearly changes in the degree of targeting from the benchmark year. The key parameter γ_s^H tests for changes in targeting, particularly for villages with characteristics indicated by V_j. The simple year effects are captured by α_s^H, and changes in targeting that are correlated with the village selection process are tested by δ_s^H. The benchmark year is 1994 when retrospective data is used. With the contemporaneous data, the benchmark year is set to be 1995, and changes in targeting between 1995 and 1996 are examined.[45] One advantage of using the retrospective data is the ability to include household, instead of village, fixed effects, as follows:

$$\begin{aligned} Y_{ijt} = {} & \sum_{s=95}^{96} [\alpha_s^H T_s + \beta_s^H (X_{ijt} \times T_s) + \gamma_s^H (X_{ijt} \times V_j \times T_s) \\ & + \delta_s^H (X_{ijt} \times D_j \times T_s)] + \mu_i^H + \epsilon_{ijt}^H. \end{aligned} \tag{4}$$

[44] A nonlinear estimation of eqq. (1) and (2) yields qualitatively consistent results. A conditional logit model is used for the household-level analysis of eligibility and participation. A Tobit model with province dummies is used for the household-level analysis of loan size (with the censoring at zero) and for the village-level analysis of the share of benefits and beneficiaries (with the censoring at zero and one).

[45] Another difference between retrospective- and contemporaneous-data-based specifications is that the dummy variable indicating households observed in 1997, as well as its interaction with the predicted PCE level, are included only in the retrospective-data-based specification. These variables control for a possible difference in the outcomes due to the timing of the survey because in the retrospective-data-based specification the benefit receipt information for 1994 or 1995 comes from both the 1996 and

In equation (4), the benchmark relationship for 1994 cannot be estimated, but changes between 1994 and 1995 as well as between 1994 and 1996 reflect the estimates controlling for the unobserved, time-invariant propensity for a household to benefit from the program.

The village-level analysis is similarly adjusted to incorporate the time dimensions. First, the subdistrict fixed effects model is estimated on both contemporaneous and retrospective data, as follows:

$$Y_{jkt} = \alpha_{94}^{V} + \gamma_{94}^{V} V_j + \delta_{94}^{V} D_j + \sum_{s=95}^{96} [\alpha_s^V T_s + \gamma_s^V (V_j \times T_s) + \delta_s^V (D_j \times T_s)] + \mu_k^V + \epsilon_{jkt}^V. \quad (5)$$

As with the household-level analysis, the benchmark year is 1994 for the retrospective data and 1995 for the contemporaneous data. The parameter of interest, γ_s^V, indicates changes in the relationship between the initial local conditions and the targeting measures. In addition, the retrospective data can incorporate village fixed effects, instead of subdistrict fixed effects, as follows:

$$Y_{jt} = \sum_{s=95}^{96} [\alpha_s^V T_s + \gamma_s^V (V_j \times T_s) + \delta_s^V (D_j \times T_s)] + \mu_j^V + \epsilon_{jt}^V. \quad (6)$$

The correlation between the outcome and village characteristics cannot be estimated for 1994, but γ_s^V for 1995 and 1996 can be computed while controlling for village-level unobserved, time-invariant factors.[46]

B. Results on Changes in Targeting Performance

I first discuss the results based on retrospective data; I then show that the results for the major findings are consistently found in the contemporaneous-data-based analysis (tables 4 and 5). The results of estimating equation (3) with retrospective data confirm that the average degree of targeting declined (table 4).[47] In 1994, for the average village, a household with one standard deviation lower PCE was 2.6 percentage points more likely to receive a loan, and the expected loan size was Rp. 7,330 larger (cols. 1 and 4). These figures fell to 2.2 percentage points and Rp. 5,835 in 1995 and to 2.1 percentage

1997 SUSENAS. The results show that households in the 1997 SUSENAS are more likely to receive benefits and achieve better targeting.

[46] Nonlinear specifications of eqq. (3) and (5) result in qualitatively same conclusions.

[47] The average degree of targeting for the benchmark year is calculated as $\beta_{94}^H + (\gamma_{94}^H \times \bar{V}) + (\delta_{94}^H \times \bar{D})$, its change between 1994 and 1995 (1994 and 1996) as $\beta_{95}^H + (\gamma_{95}^H \times \bar{V}) + (\delta_{95}^H \times \bar{D})$ ($\beta_{96}^H + (\gamma_{96}^H \times \bar{V}) + (\delta_{96}^H \times \bar{D})$). Here $\bar{V}$ and $\bar{D}$ are the average characteristics of the sample villages in the 1996 and 1997 SUSENAS.

TABLE 4

CHANGES IN THE HETEROGENEITY BY VILLAGE CHARACTERISTICS IN THE RELATIONSHIP BETWEEN PREDICTED HOUSEHOLD PCE AND IDT PARTICIPATION AND LOAN SIZE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = HOUSEHOLD; VILLAGE-LEVEL FIXED EFFECTS MODEL, BASED ON RETROSPECTIVE BENEFIT RECEIPT DATA

	Participation			Loan Size Including Zeros		
	1994 Benchmark (1)	1994–95 Deviation (2)	1994–96 Deviation (3)	1994 Benchmark (4)	1994–95 Deviation (5)	1994–96 Deviation (6)
Average degree of targeting	−.026	.004	.005	−7.330	1.494	3.252
p-value	.000	.000	.005	.000	.181	.092
Selected estimates for eq. (3):						
Year dummy		−.015*	.012+		−6.049*	5.286
		(.004)	(.006)		(2.123)	(4.463)
Predicted standardized household PCE	−.033*	.018	.021	−5.95	13.329	9.319
	(.008)	(.010)	(.014)	(6.449)	(8.500)	(11.368)
The interaction between the predicted household PCE and:						
Village-level average predicted PCE (1995 Jakarta prices, standardized)	−.004*	.000	.000	−1.433	.426	−1.393
	(.001)	(.002)	(.002)	(.826)	(1.387)	(2.215)
Village-level coefficient of variation in the predicted PCE (standardized)	−.006*	.001	.000	−1.422	1.008	.086
	(.001)	(.001)	(.002)	(.750)	(1.016)	(1.383)
Population (1,000 persons)	.002*	−.001+	.001	.525*	−.130	1.151+
	(.000)	(.000)	(.001)	(.145)	(.153)	(.477)
Density (100 persons per hectare)	−.051+	.034+	.054	−15.262+	4.329	27.658
	(.020)	(.014)	(.030)	(6.176)	(5.413)	(18.955)
Village head is aged 39 or less	.001	.000	.002	−1.694	−.31	2.376
	(.003)	(.004)	(.006)	(2.758)	(3.434)	(6.289)

Village head is aged 39 or less and completed high school or higher education	$-.009^{+}$	$.011^{+}$	.005	.492	2.002	−2.081
	(.004)	(.004)	(.007)	(2.806)	(4.545)	(6.108)
Village head is aged 40–47	.001	.003	−.005	1.341	2.563	−7.769
	(.003)	(.004)	(.006)	(2.643)	(3.494)	(6.561)
Village head is aged 40– 47 and completed junior high school or higher education	−.002	−.003	.004	−.655	−3.704	4.714
	(.003)	(.005)	(.007)	(2.063)	(3.183)	(5.277)
Village head is aged 48 and above and completed junior high school or higher education	−.001	−.001	−.006	−1.764	−.398	−.536
	(.003)	(.004)	(.006)	(2.988)	(3.704)	(6.178)
Village head is female	−.006	−.004	.035	−1.111	−1.496	3.810
	(.009)	(.010)	(.019)	(4.138)	(6.603)	(8.373)
Village government (LKMD) is established × outside of Java	.001	−.002	.003	−1.004	−2.267	−4.377
	(.002)	(.003)	(.005)	(2.408)	(3.220)	(5.009)
Village government (LKMD) is established × Java	−.020*	.003	$.027^{+}$	-4.981^{+}	2.005	9.104
	(.007)	(.008)	(.012)	(2.499)	(3.590)	(8.685)
F-statistic			11.68			5.51

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.

Note. Number of observations = 238,752; number of villages = 4.712. See the note for appendix table A1 for definitions of the outcome and explanatory variables. A selected set of estimates for eq. (3) is shown together with the average degree of targeting and the *p*-value for the test of whether the average degree of targeting is zero. See n. 47 for the computation of the average degree of targeting. The regression equations include the same set of village characteristics as table 2, which are interacted with the household relative poverty level. In addition, the triple interaction terms between the village characteristics, household relative poverty level, and the 1995 and 1996 year dummies are included. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. Standard errors are in parentheses.

$^{+}$ Significant at the 10% level.

* Significant at the 5% level.

TABLE 5

CHANGES IN THE ASSOCIATION BETWEEN VILLAGE CHARACTERISTICS AND THE SHARES OF BENEFICIARIES AND BENEFITS FOUND IN THE BOTTOM FOUR DECILES OF PREDICTED HOUSEHOLD PCE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = VILLAGE; SUBDISTRICT-LEVEL FIXED EFFECTS MODEL, BASED ON RETROSPECTIVE BENEFIT RECEIPT DATA

	Poor Households = PCE Is Below 20th Percentile						Poor Households = PCE Is Below 40th Percentile					
	Share of Participating Households That Are Poor			Share of Loan Money Provided to the Poor			Share of Participating Households That Are Poor			Share of Loan Money Provided to the Poor		
	1994 Benchmark (1)	1994–95 Deviation (2)	1994–96 Deviation (3)	1994 Benchmark (4)	1994–95 Deviation (5)	1994–96 Deviation (6)	1994 Benchmark (7)	1994–95 Deviation (8)	1994–96 Deviation (9)	1994 Benchmark (10)	1994–95 Deviation (11)	1994–96 Deviation (12)
Year dummy		−.094	−.076		−.085	−.083		−.054	−.055		−.035	−.054
		(.049)	(.067)		(.052)	(.069)		(.057)	(.078)		(.060)	(.080)
Village-level average predicted PCE (1995 Jakarta prices, standardized)	.032*	−.018	−.003	.033*	−.019	−.006	.035*	−.014	.004	.039*	−.015	.000
	(.010)	(.010)	(.015)	(.010)	(.011)	(.015)	(.011)	(.012)	(.016)	(.012)	(.012)	(.017)
Village-level coefficient of variation in the predicted PCE (standardized)	−.002	.007	−.004	−.001	.007	−.004	.013	−.014	.003	.009	−.013	.006
	(.006)	(.008)	(.010)	(.007)	(.009)	(.011)	(.007)	(.010)	(.012)	(.008)	(.010)	(.012)
Population (1,000 persons)	−.001	.002	−.003	−.001	.003	−.005	−.005	.000	.006	−.005	.001	.004
	(.004)	(.003)	(.006)	(.004)	(.003)	(.006)	(.005)	(.004)	(.008)	(.005)	(.004)	(.009)
Density (100 persons per hectare)	.142	−.178	−.001	.127	−.205	.018	.278	−.166	.065	.247	−.206	.052
	(.142)	(.122)	(.168)	(.141)	(.122)	(.170)	(.181)	(.137)	(.256)	(.180)	(.138)	(.271)
Village head is aged 39 or less	−.005	.008	.000	−.009	.010	.002	.016	−.056+	−.051	.017	−.050	−.052
	(.017)	(.024)	(.030)	(.019)	(.025)	(.031)	(.020)	(.027)	(.034)	(.022)	(.028)	(.035)
Village head is aged 39 or less and completed high school or higher education	.022	−.051	.020	.028	−.062+	.017	−.006	−.010	.056	−.006	−.022	.059
	(.020)	(.026)	(.034)	(.021)	(.027)	(.034)	(.023)	(.030)	(.038)	(.024)	(.030)	(.039)

Village head is aged 40–47	−.011	.009	.025	−.012	.006	.002	.021	−.048	−.024	.013	−.043	−.040
	(.019)	(.025)	(.030)	(.019)	(.026)	(.031)	(.021)	(.028)	(.035)	(.022)	(.029)	(.036)
Village head is aged 40–47 and completed junior high school or higher education	.017	−.007	−.028	.010	−.005	.008	.007	.023	−.013	.006	.022	.019
	(.021)	(.027)	(.032)	(.021)	(.028)	(.032)	(.025)	(.032)	(.038)	(.025)	(.033)	(.039)
Village head is aged 48 and above and completed junior high school or higher education	.005	−.011	−.008	.004	−.016	−.003	.028	−.073[+]	−.035	.026	−.074[+]	−.025
	(.024)	(.029)	(.035)	(.024)	(.030)	(.036)	(.027)	(.032)	(.039)	(.028)	(.033)	(.040)
Village head is female	−.039	.014	−.075	−.038	.008	−.073	−.024	.025	−.096	−.020	.013	−.111
	(.036)	(.047)	(.044)	(.038)	(.051)	(.050)	(.053)	(.059)	(.087)	(.054)	(.060)	(.090)
Village government (LKMD) is established × outside of Java	−.002	−.025	−.008	.008	−.027	−.003	−.006	.010	−.034	.004	.004	−.032
	(.018)	(.020)	(.023)	(.019)	(.021)	(.024)	(.022)	(.024)	(.028)	(.023)	(.025)	(.029)
Village government (LKMD) is established × Java	.005	.111	.124	.023	.100	.111	−.075	.052	.039	−.08	.041	.016
	(.108)	(.081)	(.090)	(.106)	(.082)	(.091)	(.129)	(.077)	(.093)	(.133)	(.078)	(.095)
F-statistic			1.87			1.87			1.85			1.82

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.

Note. Number of observations = 5,926; number of villages = 3,430. See the note for appendix table A1 for definitions of the outcome and explanatory variables. A selected set of estimates for eq. (5) is shown. The regression equations include the same set of village characteristics as table 2, except for the dummy variables indicating villages newly added in 1995 and 1996. These dummy variables are dropped because all the year × village observations included in the regression take the value of one. The regression equations also include the interaction terms between the village characteristics and the 1995 and 1996 year dummies. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. Standard errors are in parentheses.

[+] Significant at the 10% level.

* Significant at the 5% level.

points and Rp. 4,077 in 1996 (cols. 2–3 and 5–6). Although inaccurately estimated, the year effects in equation (5) consistently indicate a decline in the share of beneficiaries accruing to relatively poor households (table 5).

One of the main findings is that the deterioration in targeting was not concentrated in wealthier or more unequal villages. For example, the household-level analysis suggests these villages better targeted relatively poor households in 1994 (table 4). A one standard deviation increase in the average PCE is correlated with a 0.4 percentage point increase in the probability of receiving a loan in that year for a marginally poorer household—equivalent to a 15% improvement compared to the 1994 average degree of targeting. A one standard deviation increase in the coefficient of variation in the PCE is also associated with a 23% improvement. The results for 1995 and 1996 indicate these advantages did not change over time. The village-level analysis indicates a consistent tendency for wealthier villages to allocate more benefit to the poor from the beginning and not change the allocation pattern. For instance, the share of participating households whose predicted PCE is in the bottom quintile is 3 percentage points (13% of the 1994 average share) higher in villages with one standard deviation higher average PCE (table 5). This pattern was not significantly altered in later years.

In contrast, a relatively large decline in targeting is found in villages with young, educated heads (aged 39 or less and completed high school or higher education). These villages provided more loan opportunities to the relatively poor in 1994 (table 4). The probability of receiving a loan was higher for a marginally poorer household by 0.8 percentage point (31% of the 1994 average degree of targeting) compared to villages with older heads (aged 48 and above) who had relatively low educational attainment in that cohort (less than junior high school completion). However, this advantage was offset by a 1.1 and 0.7 percentage point decline in 1995 and 1996, respectively, in the tendency for a marginally poor household to receive a loan. The village-level analysis consistently suggests a 5.2 percentage point decline (20% of the 1994 average share) in the share of loan money provided to the bottom quintile in these villages between 1994 and 1995 (col. 5, table 5). Some other village characteristics are found to be correlated with targeting performance in only one of the specifications.[48]

These results are generally found when fixed effects at a more disaggregated level are incorporated (tables 6 and 7). That is, overall targeting declined, and it was concentrated in villages with young, educated heads. For example, the results

[48] For example, only the household-level analysis indicates that villages with high density and villages in Java with self-reported administrative competency exhibited a decline in targeting performance (table 4). However, only the village-level analysis results indicate that villages with older, educated heads experienced a reduction in the share of benefits accruing to the bottom two quintiles (table 5).

TABLE 6

CHANGES IN THE HETEROGENEITY BY VILLAGE CHARACTERISTICS IN THE RELATIONSHIP BETWEEN PREDICTED HOUSEHOLD PCE AND IDT PARTICIPATION AND LOAN SIZE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = HOUSEHOLD; HOUSEHOLD-LEVEL FIXED EFFECTS MODEL, BASED ON RETROSPECTIVE BENEFIT RECEIPT DATA

	Participation		Loan Size Including Zeros	
	1994–95 Deviation (1)	1994–96 Deviation (2)	1994–95 Deviation (3)	1994–96 Deviation (4)
Average degree of targeting	.004	.006	1.494	3.512
p-value	.000	.004	.181	.077
Selected estimates for eq. (4):				
Year dummy	−.015*	.012+	−6.049*	5.286
	(.004)	(.006)	(2.123)	(4.463)
Predicted standardized household PCE	.018	.024	13.329	8.755
	(.010)	(.015)	(8.499)	(13.468)
Interaction between the predicted household PCE and:				
Village-level average predicted PCE (1995 Jakarta prices, standardized)	.000	.000	.426	−1.383
	(.002)	(.003)	(1.387)	(2.369)
Village-level coefficient of variation in the predicted PCE (standardized)	.001	.001	1.008	.699
	(.001)	(.002)	(1.016)	(1.569)
Population (1,000 persons)	−.001+	.000	−.130	−.004
	(.000)	(.001)	(.153)	(.536)
Density (100 persons per hectare)	.034+	.064+	4.329	24.245
	(.014)	(.029)	(5.412)	(23.863)
Village head is aged 39 or less	.000	.002	−.310	3.751
	(.004)	(.006)	(3.433)	(7.027)
Village head is aged 39 or less and completed high school or higher education	.011+	.003	2.002	−3.717
	(.004)	(.007)	(4.545)	(6.511)
Village head is aged between 40–47	.003	−.007	2.563	−11.706
	(.004)	(.006)	(3.493)	(7.119)
Village head is aged between 40–47 and completed junior high school or higher education	−.003	.003	−3.704	8.772
	(.005)	(.007)	(3.183)	(5.554)
Village head is aged 48 and above and completed junior high school or higher education	−.001	−.006	−.398	−.352
	(.004)	(.007)	(3.704)	(6.691)
Village head is female	−.004	.036	−1.496	3.159
	(.010)	(.021)	(6.602)	(7.889)
Village government (LKMD) is established × outside of Java	−.002	.003	−2.267	−1.364
	(.003)	(.005)	(3.220)	(5.590)
Village government (LKMD) is established × Java	.003	.021	2.005	5.513
	(.008)	(.012)	(3.590)	(7.074)
F-statistic		5.11		2.22

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.

Note. Number of observations = 238,572; number of villages = 4,712. See the note for appendix table A1 for definitions of the outcome and explanatory variables. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. A selected set of estimates for eq. (4) is shown together with the average degree of targeting and the *p*-value for the test of whether the average degree of targeting is zero. See n. 36 for the computation of the average degree of targeting. The regression equations include the triple interaction terms between the village characteristics included in table 2, the household relative poverty level, and the 1995 and 1996 year dummies. Standard errors are in parentheses.

+ Significant at the 10% level.

* Significant at the 5% level.

TABLE 7

CHANGES IN THE ASSOCIATION BETWEEN VILLAGE CHARACTERISTICS AND THE SHARES OF BENEFICIARIES AND BENEFITS FOUND IN THE BOTTOM FOUR DECILES OF PREDICTED HOUSEHOLD PCE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = VILLAGE; VILLAGE-LEVEL FIXED EFFECTS MODEL, BASED ON RETROSPECTIVE BENEFIT RECEIPT DATA

	Poor Households = PCE Is Below 20th Percentile				Poor Households = PCE Is Below 40th Percentile			
	Share of Participating Households That Are Poor		Share of Loan Money Provided to the Poor		Share of Participating Households That Are Poor		Share of Loan Money Provided to the Poor	
	1994–95 Deviation (1)	1994–96 Deviation (2)	1994–95 Deviation (3)	1994–96 Deviation (4)	1994–95 Deviation (5)	1994–96 Deviation (6)	1994–95 Deviation (7)	1994–96 Deviation (8)
Year dummy	−.134+	−.152	−.122+	−.154	−.081	−.077	−.056	−.059
	(.057)	(.087)	(.061)	(.090)	(.066)	(.103)	(.069)	(.105)
Village-level average predicted PCE (1995 Jakarta prices, standardized)	−.011	.001	−.014	−.001	−.008	.025	−.010	.020
	(.012)	(.019)	(.012)	(.019)	(.013)	(.021)	(.013)	(.021)
Village-level coefficient of variation in the predicted PCE (standardized)	.002	−.015	.003	−.012	−.016	−.003	−.014	.002
	(.010)	(.014)	(.010)	(.015)	(.011)	(.016)	(.011)	(.017)
Population (1,000 persons)	.004	−.005	.005	−.006	.004	.009	.004	.009
	(.003)	(.007)	(.003)	(.008)	(.003)	(.010)	(.003)	(.011)
Density (100 persons per hectare)	−.258+	−.139	−.271+	−.102	−.293+	−.238	−.319*	−.233
	(.124)	(.179)	(.124)	(.181)	(.119)	(.281)	(.121)	(.307)
Village head is aged 39 or less	.019	.051	.021	.047	−.041	.003	−.031	.001
	(.028)	(.040)	(.029)	(.041)	(.031)	(.045)	(.032)	(.046)
Village head is aged 39 or less and completed high school or higher education	−.049	.014	−.062+	.009	−.019	.008	−.033	.000
	(.029)	(.042)	(.030)	(.043)	(.033)	(.048)	(.034)	(.049)

Village head is aged between 40–47	−.002	.039	−.008	.012	−.055	−.028	−.050	−.049
	(.029)	(.043)	(.030)	(.043)	(.032)	(.047)	(.033)	(.049)
Village head is aged 40–47 and completed junior high school or higher education	.001	−.003	.000	.027	.031	−.007	.027	.020
	(.030)	(.042)	(.031)	(.042)	(.036)	(.050)	(.037)	(.051)
Village head is aged 48 and above and completed junior high school or higher education	−.007	.006	−.010	.005	−.071+	−.038	−.069	−.035
	(.032)	(.046)	(.034)	(.047)	(.034)	(.051)	(.036)	(.053)
Village head is female	.040	−.039	.034	−.051	.035	−.027	.017	−.056
	(.053)	(.056)	(.058)	(.061)	(.064)	(.110)	(.066)	(.114)
Village government (LKMD) is established × outside of Java	−.031	.019	−.031	.029	.011	−.008	.005	.002
	(.022)	(.030)	(.023)	(.031)	(.026)	(.036)	(.027)	(.037)
Village government (LKMD) is established × Java	.141	.146	.129	.138	.100	.105	.092	.087
	(.087)	(.098)	(.088)	(.099)	(.081)	(.104)	(.082)	(.106)
F-statistic		1.52		1.62		1.80		1.80

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.

Note. Number of observations = 5,926; unique number of villages = 3,420. See the note for appendix table A1 for definitions of the outcome and explanatory variables. A selected set of estimates for eq. (6) is shown. The regression equations include the interaction terms between the village characteristics included in table 3 and the 1995 and 1996 year dummies. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. Standard errors are in parentheses.

+ Significant at the 10% level.

* Significant at the 5% level.

of the household fixed effects model (eq. [4]) show declines in the average degree of targeting (table 6), which are similar in size to the estimates in table 4. The village fixed effects model (eq. [6]; table 7) suggests that the share of beneficiaries belonging to the poorest quintile declined by 13 percentage points, or 52% of the 1994 average share of 26%. This is much larger than the estimates in table 5, and it suggests the decline in targeting was larger among villages that were continuously funded.[49] A particularly large deterioration in targeting was found in villages with young, educated heads, where the 1994–95 decline in the probability of receiving a loan for a marginally poor household was 1.1 percentage point larger (or 42% of the average degree of targeting; see table 6). These villages also exhibit a 4.1 percentage point larger decline (16% of the 1994 average share) in the share of benefits accruing to the poorest quintile (table 7). However, both models indicate no significant change in targeting performance in wealthy or unequal villages.

The results controlling for fixed effects at the most disaggregated level also reveal that densely populated villages experienced a large decline in targeting. For example, a one standard deviation in the density measure (six more persons per hectare) is associated with 0.2 percentage point (8% of the 1994 average degree of targeting) decline in the likelihood of receiving a loan for a marginally poorer household (table 6, col. 1) and a 1.5 percentage point (6% of the 1994 average share) decline in the share of participants that are from the poorest quintile (table 7, col. 1).[50]

Finally, the results based on contemporary data indicate consistent results for the major correlates of benefit allocation. First, villages with a higher level of average PCE exhibit better targeting in 1995, and this relationship does not generally change between 1995 and 1996 (tables 8 and 9). The household-level analysis suggests a similar pattern for unequal villages as well (table 8). Second, villages headed by young, educated persons generally indicate an insignificant improvement between 1995 and 1996. This is not inconsistent with the results based on the retrospective data, which suggest a similar, insignificant improvement in targeting between 1995 and 1996.

Some other results indicate contradicting patterns between the household- and village-level analyses. For instance, the household-level analysis shows that Javanese villages with organized local government had better targeting in 1995, which was offset in 1996. In contrast, the village-level analysis suggests the

[49] Among villages where the concentration measures were fully available for the 3 years, the share of benefits accruing to the poorest quintile changed from 26% in 1994 to 19% in 1996.

[50] The negative correlation between density and targeting is at odds with the negative association between density and corruption found in Olken (2006). This discrepancy in the results might suggest differential factors (associated with density) affecting the two outcomes.

TABLE 8

CHANGES IN THE HETEROGENEITY BY VILLAGE CHARACTERISTICS IN THE RELATIONSHIP BETWEEN PREDICTED HOUSEHOLD PCE AND IDT PARTICIPATION AND LOAN SIZE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = HOUSEHOLD; VILLAGE-LEVEL FIXED EFFECTS MODEL, BASED ON CONTEMPORANEOUS BENEFIT RECEIPT DATA

	Participation		Loan Size Including Zeros	
	1995 Benchmark (1)	1995–96 Deviation (2)	1995 Deviation (3)	1995–96 Deviation (4)
Average degree of targeting	−.019	−.006	−4.977	−3.388
p-value	.046	.0025	.411	.034
Selected estimates for eq. (3):				
Year dummy		.054*		26.034*
		(.008)		(5.073)
Predicted standardized household PCE	−.009	−.012	−.719	−3.043
	(.009)	(.015)	(3.587)	(9.870)
The interaction between the predicted household PCE and:				
Village-level average predicted PCE (1995 Jakarta prices, standardized)	−.005*	.000	−.996	−1.840
	(.002)	(.003)	(.629)	(2.275)
Village-level coefficient of variation in the predicted PCE (standardized)	−.004*	−.003	.053	−2.652+
	(.001)	(.002)	(.554)	(1.320)
Population (1,000 persons)	.000	.003*	.111	1.632*
	(.000)	(.001)	(.094)	(.468)
Density (100 persons per hectare)	.003	−.003	−2.259	13.415
	(.011)	(.026)	(2.760)	(16.711)
Village head is aged 39 or less and completed high school or higher education	−.003	−.002	−1.435	−.445
	(.005)	(.007)	(1.833)	(6.011)
Village head is aged 40–47	.005	−.010	.268	−6.633
	(.004)	(.007)	(1.975)	(6.256)
Village head is aged 40–47 and completed junior high school or higher education	−.009+	.011	−1.927	5.892
	(.005)	(.007)	(2.345)	(5.391)
Village head is aged 48 and above and completed junior high school or higher education	.001	−.009	.322	−2.833
	(.005)	(.007)	(1.287)	(5.488)
Village head is female	−.002	.030	−1.108	3.750
	(.014)	(.019)	(4.069)	(6.914)
Village government (LKMD) is established × outside of Java	−.001	.005	1.517	−7.099
	(.003)	(.005)	(1.301)	(4.625)
Village government (LKMD) is established × Java	−.020*	.027+	−5.570*	10.239
	(.007)	(.013)	(2.095)	(9.503)
F-statistic		7.81		4.14

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.
Note. Number of observations = 95, 868; number of villages = 4,712. See the note for appendix table A1 for definitions of the outcome and explanatory variables. All loan, grant, and PCE values are in terms of 1,000 rupiah, 1995 prices. A selected set of estimates for eq. (3) is shown, where the benchmark year is set to be 1995, and contemporaneous data is used. Also shown are the average degree of targeting and the *p*-value for the test of whether the average degree of targeting is zero. See n. 47 for the computation of the average degree of targeting.The regression equations include the same set of village characteristics as table 2, which are interacted with the household relative poverty level. In addition, the triple interaction terms between the village characteristics, household relative poverty level, and the 1996 year dummy are included. Standard errors are in parentheses.
+ Significant at the 10% level.
* Significant at the 5% level.

TABLE 9

CHANGES IN THE ASSOCIATION BETWEEN VILLAGE CHARACTERISTICS AND THE SHARES OF BENEFICIARIES AND BENEFITS FOUND IN THE BOTTOM FOUR DECILES OF PREDICTED HOUSEHOLD PCE (1994–96, RURAL INDONESIA); UNIT OF OBSERVATION = VILLAGE; SUBDISTRICT-LEVEL FIXED EFFECTS MODEL, BASED ON CONTEMPORANEOUS BENEFIT RECEIPT DATA

	Poor Households = PCE Is Below 20th Percentile				Poor Households = PCE Is Below 40th Percentile			
	Share of Participating Households That Are Poor		Share of Loan Money Provided to the Poor		Share of Participating Households That Are Poor		Share of Loan Money Provided to the Poor	
	1995 Benchmark (1)	1995–96 Deviation (2)	1995 Benchmark (3)	1995–96 Deviation (4)	1995 Benchmark (5)	1995–96 Deviation (6)	1995 Benchmark (7)	1995–96 Deviation (8)
Year dummy		.075		.040		−.160		−.112
		(.084)		(.098)		(.109)		(.114)
Village-level average predicted PCE (1995 Jakarta prices, standardized)	.036[+]	.034	.043[+]	.033	.074*	−.006	.081*	.000
	(.016)	(.019)	(.017)	(.019)	(.020)	(.023)	(.021)	(.023)
Village-level coefficient of variation in the predicted PCE (standardized)	−.017	.024	−.018	.026	.004	.024	−.002	.029
	(.010)	(.014)	(.011)	(.014)	(.013)	(.017)	(.014)	(.017)
Population (1,000 persons)	−.004	.007	−.003	.008	−.006	.002	−.006	.003
	(.004)	(.006)	(.004)	(.007)	(.005)	(.009)	(.005)	(.009)
Density (100 persons per hectare)	.186	.143	.156	.118	.187	.279	.135	.174
	(.174)	(.155)	(.180)	(.164)	(.214)	(.210)	(.227)	(.204)
Village head is aged 39 or less	−.043	.012	−.026	−.004	−.019	−.027	.012	−.054
	(.032)	(.036)	(.035)	(.039)	(.035)	(.043)	(.037)	(.046)

Village head is aged 39 or less and completed high school or higher education	−.018	.040	−.034	.053	−.056	.097	−.071	.115⁺
	(.032)	(.044)	(.035)	(.047)	(.037)	(.051)	(.040)	(.053)
Village head is aged 40–47	−.032	.048	−.038	.036	−.016	.039	−.018	.018
	(.032)	(.038)	(.033)	(.039)	(.037)	(.046)	(.038)	(.048)
Village head is aged 40–47 and completed junior high school or higher education	.026	−.069	.033	−.053	−.033	.004	−.010	.016
	(.035)	(.043)	(.036)	(.044)	(.039)	(.049)	(.040)	(.051)
Village head is aged 48 and above and completed junior high school or higher education	−.042	.014	−.058	.039	−.096⁺	.099⁺	−.098⁺	.117⁺
	(.032)	(.037)	(.032)	(.038)	(.040)	(.049)	(.041)	(.050)
Village head is female	−.049	−.066	−.079	−.043	−.104	−.007	−.144⁺	.008
	(.049)	(.052)	(.051)	(.055)	(.061)	(.087)	(.063)	(.087)
Village government (LKMD) is established × outside of Java	−.016	−.002	−.019	.016	−.034	−.051	−.029	−.048
	(.027)	(.026)	(.027)	(.027)	(.032)	(.033)	(.033)	(.034)
Village government (LKMD) is established × Java	−.147	.166	−.125	.161	−.428*	.114	−.441⁺	.130
	(.085)	(.095)	(.084)	(.097)	(.166)	(.177)	(.172)	(.177)
F-statistic		2.12		2.13		2.39		2.33

Sources. 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.
Note. Number of observations = 2,646; number of subdistricts = 2,437. See the note for appendix table A1 for definitions of the outcome and explanatory variables. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 prices. A selected set of estimates for eq. (5) is shown, where the benchmark year is set to be 1995, and the contemporaneous data are used. The regression equations include the interaction terms between the village characteristics included in table 3 and their interaction terms with the 1996 year dummy. Standard errors are in parentheses.
⁺ Significant at the 10% level.
* Significant at the 5% level.

opposite pattern.[51] These results might be due to the fact that the contemporaneous-data-based analysis involves the comparison of benefit allocation in two different sets of villages, yet unobserved effects cannot be controlled at the most disaggregated level. In contrast, the analysis using retrospective data compares outcomes over time in the same set of villages and takes into account unobserved effects at the most disaggregated level. Therefore, the results might suggest that the retrospective data provide a more reliable basis for analyzing the relationship between changes in targeting and initial community conditions.

VII. Conclusions

Given the growing popularity of community-based development and resource allocation, the ability of poor communities to implement social programs has never been more critical. This article has investigated the initial local conditions associated with community-based targeting performance using Indonesia's antipoverty program, IDT. Using the rich information on preprogram conditions, I have shown that in wealthier and more unequal villages more resources tend to be provided to households that are relatively poor within the village. These results suggest that, though there is much concern about local capture in communities with large inequality, the ease of identifying the poor could overwhelm the possible political influence of local elites. The results are robust—controlling for an extensive set of other village attributes does not alter the relationship between within-village targeting and the levels of poverty and inequality.

The lack of evidence for elite capture may appear inconsistent with results from some previous studies.[52] However, recent empirical studies do not always find a negative relationship between targeting and inequality (Coady et al. 2004; Bardhan and Mookherjee 2006). Hence, my findings, in light of the previous research, suggest that the relationship between inequality and targeting might also be specific both to local and program contexts. The nature of IDT benefits (loans) as a private good might be attributable to the positive relationship between inequality and targeting (Bardhan and Mookherjee 2006).[53] Indonesia's political context also provides one possible explanation: within-village inequality was not correlated with elite capture because village leaders had incentives to follow the national guidelines of targeting the poor. Further evidence is needed to understand whether heterogeneity is consistently

[51] Villages with educated, older heads are found to have had worse targeting in 1995 in the village-level analysis, but this is not found in the household-level analysis.
[52] Galasso and Ravallion (2005). Also, see n. 2.
[53] Olken (2007) points to the possibility that citizens monitor government compensation of labor more carefully than they do the procurement of capital (which is close to a public good).

found in the relationship between targeting and inequality depending on the nature of the benefits and the incentives given to local agents.

Exploiting the panel data on targeting performance, I have also demonstrated that targeting has deteriorated over time. One possible explanation is that demand for IDT loans exceeded the value of IDT funds in the initial year, and the poorest households were prioritized.[54] According to the preferred specification, which uses retrospective data and controls for fixed effects at the most disaggregated level, the decline in targeting was not concentrated in wealthier villages, where better targeting was constantly found during the program period. The household-level analysis suggests a similar pattern for unequal villages as well. The decline in targeting occurred partly because the successful performance, associated with young, educated village heads, did not last. A possible reason for the disappearance of the initial achievement is the program design, which provided the village heads with poor monitoring ability in later years. That is, they led the selection of eligible households in the initial year but did not directly monitor loan allocation in later years when it was instead done by community group leaders.[55]

This program design might be also related to the disproportionate targeting deterioration in densely populated villages. A possible explanation is that density is negatively correlated with the strength of social ties between the village heads and villagers (including community group leaders). Thus, in more densely populated villages, these leaders might have felt a weaker obligation to adhere to the national guidelines of targeting relatively poor households. To the extent that the findings reflect these pathways, they suggest that any possible gain from the more loyal or benevolent local agents could be diminished if a program design does not facilitate the monitoring of benefit allocations by these agents.

These findings, in turn, give rise to issues as to whether community-based targeting could generally be improved by training village heads and officials,

[54] It is possible that initial loan recipients became nonpoor as a result of benefit receipt and thus were not given additional loans in later years. However, given the average effect of IDT on poverty was very limited (Yamauchi 2008), it is unlikely that this was the main factor of the overall targeting deterioration.

[55] It is unclear why the initial advantage is found only for young, educated village heads. On the one hand, Indonesia's historical context suggests that these heads might have had better administration skills and stronger loyalty to the national government because they often replaced traditional, inward-looking village heads in the 1980s and were particularly loyal to the central government (Husken 1994; Antlov 1995). On the other hand, it is also possible that they had a stronger preference for a more democratic selection. Rao and Ibanez (2005) discuss "benevolent capture," in which influential individuals dominate community-level decision making, while also taking into account the best interests of the community.

modifying program design and instructions, and strengthening monitoring by upper-level government and local agents.[56] Empirical evidence on these issues from a broad range of settings is likely to enhance the utilization of local knowledge and thus the implementation of community-based social programs.

[56] Olken (2007, 2008) addresses these issues in the context of corruption and project choice based on the sample of Indonesian villages from two provinces. Ravallion (2000) shows the effects of monitoring and budget expansion for Argentina.

Appendix A
Supplementary Tables

TABLE A1
SUMMARY STATISTICS OF OUTCOME VARIABLES FOR RURAL INDONESIA (1997)

	N	Mean	SD
Household-level outcome:			
Household is eligible (someone is a member of an IDT community group)	46,836	.408	.491
Household has someone participating in IDT (receiving a loan)	46,836	.343	.475
Cumulative loan value among participants (Rp. 1,000, 1995)	16,048	468	972
Cumulative loan value among all (Rp. 1,000, 1995), including zeros	46,836	160	611
Village-level outcome:			
Share of eligible households whose PCE is less than the 20th percentile	2,382	.235	.193
Share of eligible households whose PCE is less than the 40th percentile	2,382	.447	.227
Share of participating households whose PCE is less than the 20th percentile	2,241	.237	.208
Share of participating households whose PCE is less than the 40th percentile	2,241	.447	.245
Share of loan money given to households whose PCE is less than the 20th percentile	2,241	.234	.220
Share of loan money given to households whose PCE is less than the 40th percentile	2,241	.446	.259

Source. 1997 SUSENAS.
Note. N = number of observations. An eligible household has a member who belongs to a community group that was the unit of loan management under IDT. A participating household has received at least one loan by January of 1997. Cumulative loan value is the total amount of money extended as credit between the beginning of IDT and January of 1997. The 20th and 40th percentiles are measured within each village based on the predicted household PCE. The prediction is based on the relationship between the actual PCE and household characteristics in 1993 and 1994 (see Sec. III.A).

TABLE A2
SUMMARY STATISTICS OF HOUSEHOLD CHARACTERISTICS FOR RURAL INDONESIA (1997)

Household Characteristic	Mean	SD
Per capita expenditure (PCE) per month (Rp. 1,000, 1995)	41.01	23.54
Predicted PCE per month (Rp. 1,000, 1995)	40.65	14.69
Characteristics of the household head:		
Age	43.34	13.36
Age^2	2,057	1,279
Male	.89	.31
Single	.03	.16
Married	.85	.35

TABLE A2 (*Continued*)

Household Characteristic	Mean	SD
Educational attainment:		
Attended but attained no degree	.29	.46
Completed primary school	.30	.46
Completed secondary school	.17	.37
Can speak Indonesian	.83	.38
Can read and write alphabet	.73	.44
Housing quality:		
Floor area (1,000 square meters)	.05	.04
Wall is made of inferior materials	.35	.48
Roof is made of inferior materials	.30	.46
Floor is made of inferior materials	.41	.49
Inferior source of light is used	.52	.50
No toilet facility	.42	.49
Demographic characteristics:		
Household size	4.38	1.93
Share of members aged 0–4	.10	.14
Share of members aged 5–15	.24	.22
Share of female members aged 16–55	.28	.17
Share of male members aged 16–55	.27	.18
Share of female members aged 56 and over	.06	.17

Sources. 1997 SUSENAS.
Note. $N = 46{,}836$. Categories omitted in the characteristics of household heads are being widowed or divorced (marital status) and having not attended school (educational attainment).

TABLE A3

SUMMARY STATISTICS OF VILLAGE CHARACTERISTICS FOR RURAL INDONESIA (1997)

Village Characteristic	Mean	SD
Characteristics of and heterogeneity in village residents:		
Imputed household per capital expenditure (PCE) (1,000 rupiah, 1995 Jakarta prices)	40.59	8.94
Coefficient of variation (CV) of imputed PCE	.29	.09
Population (1,000 persons)	2.37	2.05
Density (100 persons per hectare)	.04	.06
Share of educated household heads who have completed the primary degree or above	.47	.26
Education Gini index	.39	.22
Characteristics of village head:		
Village head is aged 39 or less	.33	.47
Village head is aged 39 or less and completed high school or higher education	.14	.35
Village head is aged 40–47	.31	.46
Village head is aged 40–47 and completed junior high school or higher education	.17	.37
Village head is aged 48 and above and completed junior high school or higher education	.16	.36
Village head is female	.01	.12

TABLE A3 (*Continued*)

Village Characteristic	Mean	SD
Characteristics of village administrative and social institutions:		
Village government (LKMD) is established} × village is outside Java	.39	.49
Village government (LKMD) is established} × village is in Java	.24	.43
Village has farmers' associations	.65	.48
Village has groups of advisors such as agricultural extension and health and nutrition	.63	.48
Availability of financial institutions:		
Village has at least one cooperative	.21	.40
Village has at least one bank	.12	.33
Village received at least one credit program in the previous year	.34	.47
Transportation and communication infrastructure:		
Village's main access is through land	.88	.33
Village's main access is through land and the inter-village road is made of asphalt or hardened	.38	.49
Village has access to public transportation within the village	.39	.49
Village has a public television	.26	.44
Village has a post office	.07	.25
Experiences of negative shocks:		
Village experienced natural disasters such as droughts, floods, earthquakes and volcano eruptions at least once in the past 3 years	.38	.49
Village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year	.23	.42
Grant receipt status:		
Village's grant status in 1993 depended on field officers' subjective perceptions	.36	.48
Village was newly added to the treatment group in 1995	.14	.35
Village was newly added to the treatment group in 1996	.25	.43
Village dropped out of the treatment group in 1995 or 1996	.04	.20
Difference between the village score and the 1993 provincial threshold	−.26	1.19
Difference between the village score and the 1994 provincial threshold	.41	1.42
Village was funded in 1993 or 1994 despite the rules suggesting no funding	.02	.12
Regional dummies:		
Sumatera	.17	.37
Java	.26	.44
Nussa Tenggara	.25	.43
Kalimantan	.11	.31
Sulawesi	.09	.29
East (omitted)		

Sources. 1997 SUSENAS and 1993 PODES.
Note. N = number of observations (village) = 2,832. See Sec. IV.B for more detailed definitions of the dummy variables indicating characteristics of village head and village administrative institutions. Among grant receipt status, only the 1993 difference between the village score and the upper provincial threshold is used because this difference is highly correlated with the difference between the score and the lower threshold. Also, other types of errors in grant status assignment are too rare to be included.

TABLE A4

PREPROGRAM RELATIONSHIP BETWEEN HOUSEHOLD PCE AND CHARACTERISTICS (1993 AND 1994, RURAL INDONESIA)

Outcome = Household PCE (1995 Prices)	Coefficient	SE
Characteristics of the household head:		
Educational attainment:		
Attended but no degree	435.27+	228.991
Primary degree	2,010.05**	252.682
Secondary degree	13,179.42**	267.099
Can speak Indonesian	2,616.92**	184.406
Can read and write alphabet	912.894**	240.115
Age	343.367**	21.137
Age^2	−2.811**	.220
Male	−1,333.73**	265.869
Single	5,837.89**	350.012
Married	2,686.33**	227.370
Characteristics of the housing:		
Floor area (1,000 square meters)	59,028.20**	1,082.533
Wall is made of inferior materials	−2,642.81**	115.381
Roof is made of inferior materials	−3,334.74**	130.049
Floor is made of inferior materials	−3,928.33**	113.224
Inferior source of light is used	−6,988.84**	96.036
No toilet facility	273.317**	96.056
Demographic characteristics:		
Household size = 2	−22,221.22**	258.365
Household size = 3	−30,581.71**	268.132
Household size = 4	−36,062.90**	279.765
Household size = 5	−39,750.24**	291.263
Household size = 6	−42,811.66**	305.270
Household size is 7 or above	−45,804.14**	308.762
Share of members aged 0–4	−11,669.34**	618.133
Share of members aged 5–15	−7,883.26**	529.165
Share of female members aged 16–55	−5,598.90**	538.319
Share of male members aged 16–55	8,626.81**	450.758
Share of female members aged 56 and over	−14,001.88**	551.996
No. of observations	250,974	
R^2	.8	
F-statistic	19,461.63	

Sources. 1993 and 1994 SUSENAS.

Note. The regression also includes dummy variables indicating different provinces.

+ Significant at the 10% level.

** Significant at the 1% level.

TABLE A5

HOUSEHOLD CHARACTERISTICS ASSOCIATED WITH IDT ELIGIBILITY, PARTICIPATION, AND LOAN SIZE (1997, RURAL INDONESIA)

	Household Is Eligible (1)	Household Has Participated (2)	Household Has Participated Given Eligibility (3)	Ln(Loan Size) Given Participation (4)	Loan Size Including Zeros (5)
Characteristics of the household head:					
Educational attainment:					
Attended but no degree	−1.794^{+}	−1.605	.828	.012	−29.307^{+}
	(1.039)	(1.028)	(1.035)	(.030)	(15.183)
Primary degree	−3.477**	−2.785*	1.985^{+}	.040	−25.585^{+}
	(1.152)	(1.138)	(1.127)	(.035)	(14.140)
Secondary degree	−14.206**	−12.071**	.973	.049	−65.883**
	(1.260)	(1.242)	(1.310)	(.038)	(15.632)
Can speak Indonesian	1.453^{+}	1.081	.284	−.054*	−6.518
	(.848)	(.814)	(.799)	(.023)	(10.037)
Can read and write alphabet	2.571*	2.671**	−.374	.013	30.932*
	(1.025)	(1.018)	(1.061)	(.028)	(13.540)
Age	.575**	.613**	.288**	−.004	2.463*
	(.092)	(.090)	(.106)	(.004)	(1.065)
Age^2	−.007**	−.007**	−.003**	.000	−.028*
	(.001)	(.001)	(.001)	(.000)	(.011)
Male	7.825**	6.818**	2.580*	.089*	50.274**
	(1.115)	(1.103)	(1.261)	(.036)	(11.702)
Single	−2.412^{+}	−2.109	−2.031	−.108	−22.059
	(1.373)	(1.363)	(1.893)	(.073)	(17.110)
Married	.425	.678	−.477	−.002	2.868
	(.888)	(.890)	(.948)	(.035)	(11.174)
Characteristics of the housing:					
Floor area (1,000 square meters)	−41.868**	−40.503**	3.650	−.094	−176.542**
	(6.478)	(6.306)	(7.733)	(.297)	(52.370)
Wall is made of inferior materials	5.213**	4.709**	.674	−.016	.532
	(.659)	(.648)	(.721)	(.021)	(8.086)
Roof is made of inferior materials	1.577*	1.391*	−.123	.005	17.12o^{+}
	(.661)	(.655)	(.645)	(.016)	(8.906)
Floor is made of inferior materials	5.73**	5.405**	1.174^{+}	.007	30.195**
	(.637)	(.629)	(.652)	(.016)	(7.006)
Inferior source of light is used	2.602**	1.674*	−.764	−.042*	1.503
	(.697)	(.666)	(.691)	(.021)	(8.176)
No toilet facility	2.700**	1.727**	−.962	−.036^{+}	−6.944
	(.633)	(.616)	(.684)	(.020)	(8.925)
Demographic characteristics:					
No. of household members	1.376**	1.326**	.301*	.014**	6.841**
	(.136)	(.132)	(.143)	(.004)	(1.552)
Share of members aged 0–4	6.627**	6.473**	2.878	.000	23.344
	(2.514)	(2.437)	(2.824)	(.131)	(28.163)
Share of members aged 5–15	6.384**	6.682**	3.894	.099	55.560*
	(2.173)	(2.097)	(2.435)	(.116)	(23.462)
Share of female members aged 16–55	6.623**	6.636**	4.211	.169	32.694
	(2.257)	(2.200)	(2.711)	(.123)	(23.723)
Share of male members aged 16–55	1.570	3.178^{+}	4.991*	.085	35.523
	(1.909)	(1.825)	(2.198)	(.094)	(24.061)
Share of female members aged 56 and over	−.527	1.713	7.560*	.097	2.809
	(2.312)	(2.262)	(2.956)	(.155)	(26.178)

TABLE A5 (*Continued*)

	Household Is Eligible (1)	Household Has Participated (2)	Household Has Participated Given Eligibility (3)	Ln(Loan Size) Given Participation (4)	Loan Size Including Zeros (5)
No. of observations	46,836	46,836	19,091	16,048	46,836
No. of villages	2,832	2,832	2,382	2,241	2,832
F-statistic	59.45	51.67	2.69	3.23	9.45

Sources. 1997 SUSENAS, 1993 PODES, and IDT data.
Note. The regression also includes the village-level fixed effects. All the loan values are in terms of 1,000 rupiah, 1995 prices. Standard errors are in parentheses.
$^{+}$ Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.

TABLE A6

ROBUSTNESS CHECK FOR VILLAGE CHARACTERISTICS ASSOCIATED WITH THE SHARE OF OVERALL BENEFITS FOUND IN THE BOTTOM TWO QUINTILES OF PREDICTED HOUSEHOLD PCE (1997, RURAL INDONESIA)

	Outcome = Share of Loan Money Provided to Households Whose PCE Is Below the 40th Percentile				
	(1)	(2)	(3)	(4)	(5)
Village-level average predicted PCE (1995 Jakarta prices, standardized)	.052*	.054*	.055*	.055*	.048*
	(.015)	(.017)	(.017)	(.017)	(.018)
Village-level coefficient of variation in the predicted PCE (standardized)	.022^{+}	.020^{+}	.020^{+}	.019	.018
	(.010)	(.010)	(.010)	(.010)	(.010)
Population, density, share of educated household heads, education Gini index		X	X	X	X
Characteristics of the village head, competency of village government, availability of social groups			X	X	X
Availability of credit institutions, infrastructure, communication facilities				X	X
Past income shocks, controls for the village selection process					X
F-statistic	8.53	3.32	1.52	1.48	1.34

Sources. 1997 SUSENAS, 1993 PODES, and IDT data.
Note. Number of observations = 2,241; number of subdistricts = 1,283. The regression also includes the village-level fixed effects. All the loan values are in terms of 1,000 rupiah, 1995 prices. The results for other outcomes indicate similar robustness. Standard errors are in parentheses.
$^{+}$ Significant at the 10% level.
* Significant at the 5% level.

Appendix B
Differences in the Household-Level and Village-Level Analyses
1. Difference in Neutral Allocation

The household- and village-level analyses implicitly assume that different types of allocation changes (namely, additive and proportional changes) are targeting neutral. Suppose for simplicity the following specifications:

$$Y_{ij} = \alpha_0 + \beta_0 X_{ij} + \beta_1 (X_{ij} \times V_j) + \mu_j + \epsilon_{ij}. \tag{A1}$$

$$Y_j = \alpha_0 + \beta_0 V_j + \epsilon_j. \tag{A2}$$

Suppose that the average allocation in village j is $y_j^1, \dots, y_j^{Nj}$. If villages indicated by a dummy V_j deviate from this allocation by providing α to all households, the new allocation is $y_j^1 + \alpha, \dots, y_j^{Nj} + \alpha$. Since this change is absorbed by the village fixed effects, the estimate for β_1 will be insignificant. On the other hand, this could be detected in equation (A1) as a significant change in targeting performance. Suppose that a dummy variable D_{ij} indicates relatively poor households and that a fraction s of the households are regarded as poor. Then, the concentration measure Y_j can be expressed as B_p/B where $B_p = \Sigma(y_{ij} \times d_{ij})$ and $B = \Sigma y_{ij}$. For villages indicated by V_j, the outcome variable is $(B_p'/B') = \Sigma[(y_{ij} + \alpha) \times d_{ij}]/\Sigma(y_{ij} + \alpha)$. The deviation from the overall average is $(B_p/B) - (B_p'/B') = c \times (B_p - sB)$, where $c = N_j \times (\alpha/B) \times B'$. Thus, if the average allocation does better than the universal allocation ($B_p/B > s$), the additive allocation change leads to deteriorated targeting. For example, only the village-level analysis suggests that better targeting is found in villages with a post office and in villages that experienced natural disasters (table 3). This suggests that these villages allocate less benefits (of the same size) to both the relatively poor and the relatively wealthy compared to the overall performance, and this results in an improvement of targeting measured by concentration.

On the other hand, the concentration measure regards as neutral a proportional change in which $y_{ij}' = y_{ij}\gamma$ ($\gamma > 1$). This change, however, is regarded as a deviation in equation (A1). Suppose that the demeaned data are $y_{ij}^* = y_{ij} - \bar{y}_j$ and the degree of targeting for the baseline village ($V_j = 0$) is $T = \Sigma x_{ij}^* y_{ij}^* / \Sigma x_{ij}^{*2}$. After the proportional change ($y_{ij}^{*\prime} = \gamma y_{ij}^*$), $T' = \Sigma x_{ij} \times \gamma y_{ij}^* / \Sigma x_{ij}^{*2} = \gamma T$. Thus, if $T < 0$, a proportional change is regarded as an improvement in the village fixed model. For example, only the household-level analysis indicates that better targeting is found in villages with a smaller population and previous program receipt (table 2). This suggests that villages with a smaller population attain a larger within-village gap in the probability of being a beneficiary between relatively poor and relatively wealthy households; however, the increments are proportional to the probabilities attained by these households, and thus they are not detected by the village-level analysis as targeting improving.

2. Difference in the Samples

Another methodological difference is that the village-level analysis uses villages where at least one household participates in the program. If such villages also have unobserved factors, such as a preference for wider coverage and if these systematically affect targeting, then the results without the selection correction could be biased. Unfortunately, the data do not provide a factor that induces villages to have at least one surveyed household to participate but yet does not affect targeting performance. Instead of doing the selection correction, the household-level analysis results are examined based on those villages included in the village-level analysis. In general, the results are substantively consistent.

This consistency is likely to be partly due to the fact that funding history (which is highly correlated with whether a village has at least one participant) is controlled. The results of the household-level analysis (eqq. [3] and [4]) suggest that targeting performance differed depending on funding history (not reported). That is, villages included for funding in 1995 and 1996 had exhibited poor targeting performance for the years in which they had not been funded (because no one had been a beneficiary). Villages that dropped out of the funding list showed a decline in targeting performance in later years of the program period.

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