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

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Abstract: Community-based selection of social program recipients has the potential to benefit from local knowledge about individuals in need. This informational advantage however might be offset by local elite capture and administrative incompetency. Using Indonesia's anti-poverty program, this paper investigates which pre-program conditions are associated with community-based targeting outcomes. Results show that wealthier and more unequal villages constantly target better. This suggests that, though there is much concern about local capture in communities with large inequality, the ease of identifying the poor could overwhelm the possibly larger political influence of local elites. Also, villages headed by young, educated persons initially exhibit better targeting, but lose this advantage over time, as the monitoring of loan disbursement becomes more difficult for village heads. I explore Indonesia's political context, which provides insight into these findings.

Key words: targeting, community, inequality, IDT, Indonesia
JEL Codes: D73, H11, H75, O17

1 Introduction

Recently, there has been a growing interest in the integration of community involvement in social program provision.[1] In 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 about who deserves assistance within the community relative to the central government (Alderman, 2002; Faguet, 2004). However, much anecdotal and theoretical evidence points to the possibility that local non-poor elites capture program resources,[2] particularly in communities with large economic inequality. The lack of administrative capability among local agents can also offset the informational advantage.[3] It is unclear how much and at which stages of program implementation these factors limit the effectiveness of community-based targeting. If communities with strong elites prioritize an allocation to the non-poor, assistance may only reach the intended beneficiaries at a later stage. If monitoring of benefit allocations becomes difficult for local agents over time, targeting performance may decline. Therefore, in designing community-based targeting, it is crucial to know which communities can prioritize delivery to the poor. Despite the ambiguity in the overall effectiveness of community based targeting, rigorous empirical evidence is relatively scarce on factors associated with changes in the targeting performance.

This paper fill this gap by showing how changes in targeting performance are associated with a rich array of pre-program community conditions, including inequality in consumption

[1] For instance, see Mansuri and Rao (2004) and World Bank (2000, 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 (Antlov, 2003; Conning and Kevane, 2002; Crook and Manor, 1998, among others). Bardhan and Mookherjee (2000, 2005) theoretically demonstrate that the allocation of program benefits between different groups of constituencies depends on the political influence of these groups, which in turn hinges on their political awareness and socio-economic status.

[3] For instance, see Coady, Grosh, and Hoddinott (2004) and Conning and Kevane (2002).

and education levels as well as the characteristics of local agents. In particular, I exploit the panel information on targeting outcomes of Indonesia's anti-poverty program, *Inpres Desa Terttingal* (IDT, 1994-1997). The government selected poor villages under this program for funding designated for small business loans. In turn, selected poor villages chose households eligible for loans according to their own criteria. Results show that wealthier and more unequal villages constantly target well. This suggests that inequality is not always associated with elite capture. It could be offset by targeting-improving factors in unequal villages, such as an easier identification of the poor and acceptance of placing priority on them. Evidence is also found that villages with young, educated heads initially exhibit better targeting, but lose this advantage over time, as the monitoring of loan disbursement becomes more difficult for village heads.

These findings are related to the growing literature on targeting and decentralization. Theory suggests that the degree of capture can depend on local contexts (Bardhan and Mookherjee, 2000, 2005). Indeed, a meta-analysis of targeted anti-poverty programs indicates that the performance in allocating benefits to the poor varies significantly within programs adopting the same scheme of community-based targeting (Coady et al., 2004).[4] This suggests the importance of investigating local factors that might explain this variance.[5] However, evidence from cross-sectional studies is mixed. Coady et al. (2004) find that richer, more unequal, and more accountable countries target well. On the other hand, in Bangladesh's Food-for-Education program, villages with higher inequality in landholding attain a lower participation rate for

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

[5]Jayne, Strauss, Yamano, and Molla (2001) also find a large variation in the allocation pattern across different regions in Ethiopia in its food aid / food-for-work programs.

the poor compared to the non-poor, and poorer villages show better targeting (Galasso and Ravallion, 2005).[6] In Indonesia's rice subsidy program, districts with higher ethnic fragmentation and lower density have more subsidized rice go missing before it reaches the intended beneficiaries, but the median per capita expenditure and within-district inequality are not significantly correlated with the degree of corruption (Olken, 2006).

These cross-sectional studies do not address whether targeting performance changes and which local conditions are associated with the changes.[7] A few exceptional studies include Ravallion (1999), who shows that a reduction in program budget worsened targeting performance in Argentina. Based on this finding, he points to the possibility that program resources begin to reach the poor only after the non-poor capture some share in the early stages of program implementation. 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 only in an employment generation program, but not in credit and agricultural minikit programs. Given these findings, they conclude that 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 charac-

[6] Also, in the related literature on the community-based choice of public projects, Araujo, Ferreira, Lanjouw, and Ozler (2006) report that inequality is correlated with a lower probability of receiving pro-poor projects such as latrines.

[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 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, Strauss, Yamano, and Molla (2002) investigate the relationship between current and past receipt of program resources. They find that some households are chronic beneficiaries, suggesting the possibility of aid dependence.

teristics of local agents. Related studies indicate that it is important to monitor or regulate their actions. Olken (2007) shows that monitoring by upper-level government reduces 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 and involvement of upper-level government are associated with better outcomes.[8] I explore the relationship between local agents and government of higher levels in Indonesia, which provides insight into my empirical findings.

The rest of the paper is organized as follows: section 2 describes more details of IDT, and section 3 explains the data and targeting measures used in the analysis. Followed by the illustration of empirical strategy, section 5 discusses the results for overall targeting performance. Section 6 moves on to the results for changes in targeting performance. Section 7 concludes.

2 Anti-Poverty Program for Left-behind Villages, IDT

2.1 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 "village score." Selected village were then allowed to identify households

[8]For example, Wade (1997), Parry (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 (Olken, 2008; Rosenzweig and Foster, 2003).

eligible for a loan. In order to encourage the use of local knowledge of 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 (BPS), 1994).

The scope of IDT is significant. Each selected village received Rp. 20 million (approximately US$8932) per annum.[9] With approximately one-third of Indonesia's more than 60,000 villages funded for three fiscal years, government spending on the program totalled over Rp. 1.2 trillion (US$536 million). IDT also achieved relatively wide coverage. Among selected villages, 34% of households had received an IDT loan at least once by the end of the program period, 1994-1997. This figure corresponds to 13% of all Indonesian households. Among these participants, the cumulative loan size averaged Rp.467,776, which was about 2.5 (9.8) times the average monthly household (per capita) expenditure among participating households (Appendix Table 1[A]).[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 continued to receive funding regardless of the second-year village score, a minor fraction of villages with a very small number of households ceased to

[9] This is based on the 1995 average exchange rate of Rp.2239 per 1995 dollar (Indonesian Financial Statistics, Bank Indonesia).

[10] Author's calculation based on the SUSENAS 1997.

[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 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.

receive grants based on a concern that the across-village differences in the per capita grant value were too large (Badan Pusat Statistik (BPS), 1995). My community-based (within-village) analysis uses villages that were funded at least once, and 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 sub-district government. Upon approval, the groups received funds directly through a local branch of a state-owned bank, and were responsible for loan management.[13] Most eligible households (84%) participated in the program.

Since IDT was a departure from the centralized approach, there was broad concern about the local ability to implement the program (Booth, 1994). The program was followed by a similar community-based scheme called Kecamatan Development Program (Daley and Fane, 2002), and there is an on-going call for continuing targeted poverty alleviation and a community-based development approach (World Bank, 2006).

2.2 Previous Studies on IDT

The availability of nationally representative data and the explicit, formula-based village selection rule has attracted many researchers to investigate the inter-village distribution of IDT funds; however, its within-village distribution and the association with the local conditions have not yet been investigated. For example, Alatas (2000) shows that the rules to select poor villages were closely followed, involving few errors. As a result, districts with a lower level

[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.

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 one hand, the results based on matching methods indicate few effects.[15] On the other hand, studies using the variation in per capita/household grant value find significant negative effects on poverty and inequality.[16]

3 Data and Targeting Performance

3.1 Data

My empirical analysis utilizes the following three datasets: First, information on IDT benefits and household characteristics is extracted from the 1996 and 1997 National Socio-Economic 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 that had been observed before IDT started. Third, village- and year-specific funding status is available in the IDT administrative dataset. I

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

[15]The results based on propensity-score-matching and village fixed effects show no significant effects on a number of outcomes, such as labor supply and household expenditure (Molyneaux and Gertler, 1999). Using a different matching method that utilizes the differential probability of funding across provinces, Alatas (2000) finds the 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. Interviews conducted in six provinces also indicate that participants there found that IDT loan activities were not very profitable (Badan Pusat Statistik (BPS), 1997).

[16]Larger per capita grants are correlated with a decline or slower growth in within-province inequality (Akita and Szeto, 2000). Larger per household grants are associated with disproportionate increases in the village-level average income and consumption given initial economic infrastructure (Yamauchi, 2008). No impact is found for the incidence of child labor (Yamauchi, 2007). Also, in an overview of major anti-poverty credit programs in the 1990s, Sumarto et al. (1998) conclude that IDT was relatively flexible and loan management responsibility shared among beneficiaries encouraged production activities.

combine these datasets, and focus on rural areas, which include most funded villages.[17]

Targeting measures are based on the poverty level and program benefits of a household. First, the household poverty level is defined by predicted household per capita expenditure (PCE). The predicted PCE is used because 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] Second, program benefits are measured by a household's eligibility, receipt of a loan, and loan size. The 1996 and 1997 SUSENAS asks whether anyone in a household has ever been a member of a community group for IDT (members are eligible for a loan), whether that person has received an IDT loan, and if so, the year of receipt and the yearly cumulative loan size.[21] The panel data on the distribution

[17]I do not pool rural and urban areas because they faced distinct criteria for the identification of poor communities, and 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. The retrospective information on consumption or income is also unavailable.

[19]See Appendix Table 2 for the results, and Appendix Table 1[B] for the summary statistics for household-level characteristics.

[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 educational attainment of household heads who were, on average, 43 years old. Though 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 only for a decrease in the fraction of children aged 0-4. The effects on three housing quality indicators also show insignificant changes. While another indicator shows an improvement, two other indicators exhibit deteriorations, suggesting that these changes are unlikely to be due to IDT.

[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. Though the data indicates that loan size does not vary among participants in about 15% of the sample villages, this could be the result of allocating loans of the same size. To the extent that the latter type of reporting took place and relatively wealthier households among the group kept a larger share, the targeting measures based on this information are overestimated. Thus, the

of beneficiaries and benefits are created using this information.[22]

In order to measure targeting performance, I use (1) the degree to which relatively poor households receive benefits and (2) 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.[23] The other set of targeting measures indicates the concentration of beneficiaries and benefits among relatively poor households. These measures facilitate the graphical illustration and decomposition analysis of distributional outcomes (Coady and Scoufias, 2004; Duclos, Makdissi, and Wodon, 2005).

3.2 Targeting: Overall, Inter- 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 33 percent, and the share of households that had received a loan was 28 percent for the first (poorest) decile (Fig.1A). The respective figures for the 10th (richest) decile are six and five percent. However, among loan recipient households, the poorer received smaller loans (Fig.1B). Altogether, the distribution of the average loan size including non-participants, or the unconditional loan size, exhibit a negative slope, suggesting that the pro-poor distribution of beneficiaries dominates the pro-rich

estimated targeting measures could be seen as the upper bound. Also, if such a measurement error occurred more often in villages with a particular characteristic, a true decline in targeting performance associated with that characteristic is not fully detected. Thus, if significant differences are found, they are likely to serve as the lower bound in the gap in targeting performance. The questionnaire and other documentation are available at $http://www.rand.org/labor/bps.data/webdocs/susenas/susenas_main.htm$

[22]Households in the 1996 SUSENAS report loans extended in 1994 and 1995, and those in the 1997 SUSENAS report loans extended in 1994-1996. 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-section analysis.

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

distribution of conditional loan size. Consistently, the distribution of the share of participants shows a larger deviation from the distribution that would be realized under universal distribution (depicted by the 45 degree line as a benchmark) compared to the distribution of the share of loan money (Fig.1C). The bottom 40 percent of the PCE distribution received 53 percent of the benefits. This amounts to a 32% increase compared to their share under universal provision (40 percent). The equivalent figure for the distribution of beneficiaries is 50%. 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).

The overall distribution of IDT benefits can be decomposed into an inter- and within-village allocation. I define households who are 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- and intra-village selection, the distribution of potential beneficiaries/benefits reflects only the result of inter-village selection. The ratio of the shares of potential and actual beneficiaries indicates that poorer households are more likely to not only be included in IDT villages, but also to be selected as a beneficiary within IDT villages (Fig.2A). However, this pattern is not found in the distribution of benefits. The distribution of the average unconditional loan size and the distribution of the average potential benefit value mostly match each other (Fig.2B). This suggests that the pro-poor distribution of beneficiaries within IDT villages is offset by the pro-rich distribution of loan size conditional on receipt. The concentration curves (Fig.2C) also indicate that the selection of IDT villages contributes to overall targeting.[24] The selection of

[24]The distribution of potential benefit value however does not show a further contribution. That is, conditional on grant receipt, the per household grant value does not vary across deciles. This is consistent with the

actual beneficiaries exhibits a further contribution; however, this is almost completely offset by the pro-rich distribution of loan size among beneficiaries. As a result, the overall distribution of loan money closely matches the distributions of potential beneficiaries and benefits for the first four deciles.

These results provide an indication that villages contribute to overall targeting in terms of beneficiaries, though not in terms of benefits. The analysis so far has not taken into account the fact that households from one village could 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 non-parametric and linear relationships demonstrate that the probability of participating in IDT increases by six percent as a household's relative poverty level decreases (Fig.3A).[25] As a result, 45 percent of beneficiaries are concentrated among the bottom 40 percent of the relative PCE distribution (Fig.3C). On the other hand, loan size does not vary much within a funded village (Fig.3B). This suggests that the pro-rich distribution of conditional loan size (Fig.1B) is due to larger loans provided in wealthier IDT villages. With no within-village variation in conditional loan size, unconditional loan size and the relative poverty level show a negative relationship. Since this merely reflects the pro-poor distribution of participants, the concentration curves for beneficiaries and benefits completely coincide (Fig.3C). These results confirm that there is a contribution of community-based targeting towards overall targeting, and most of the contribution arises from the selection of beneficiaries. However, once benefits are broken down by the year of receipt, the concentration curves show that targeting deteriorated over time (Fig.3D), particularly for the poorest quintile.[26]

fact that village size is not highly correlated with the PCE level.

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

[26] The distribution of the share of beneficiaries shows the same pattern of changes.

4 Empirical Strategy

4.1 Overall Benefits

I next explore which village characteristics are correlated with overall targeting before investigating which characteristics are associated with changes in targeting performance.[27] Two specifications are utilized which 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:

$$Y_{ij} = \alpha_0^H + \beta_0^H X_{ij} + \beta_1^H [X_{ij} * V_j] + \beta_2^H [X_{ij} * D_j] + \mu^H + \epsilon_{ij}^H \tag{1}$$

The outcome variable, Y_{ij}, denotes benefits for a household i in village j. It includes 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. 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}. Parameter β_1^H allows the degree of targeting to differ across villages depending on their pre-program 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

[27] The concentration measures indicate a large variation. On one hand, no eligibility (actual participation or loan money) was allocated to the bottom 40 percent of households in 8 (10) percent of targeted villages. On the other hand, all eligibility (participation or loan money) was invested in the bottom 40 percent in 7 (8) percent of the villages. Distributions better than universal allocation are found in 40 (43) percent 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).

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 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 OLS model:

$$Y_{jp} = \alpha_0^V + \beta_1^V V_{jp} + \beta_2^V D_{jp} + \mu_p^V + \epsilon_{jp}^V \qquad (2)$$

The outcome variable is the share 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 percent, in village j in province p. The parameter of interest, β_1^V, indicates the correlation between these concentration measures and pre-existing village conditions. Similarly to Eq.(1), the village selection process is controlled by including D_{jp}. The province-level dummies are also included.[29] Note that, under these two methods based on equations (1) and (2), different changes in benefit allocation are considered as targeting-neutral. While Eq. (1) takes a constant additive change as neutral, Eq. (2) takes a proportional change as neutral (See Appendix 1). The following analysis focuses on village characteristics that are consistently related to targeting performance under the two specifications.

[28] D_j includes the 1993 and 1994 differences between the village score and the provincial threshold, which represents the propensity to be funded. It also includes a dummy variable that indicates a village where funding status in 1993 depended on a field officer's subjective evaluation. Two additional dummy variables are included to indicate villages selected for funding based on the 1994 and 1995 criteria. Another dummy variable indicates villages that were once funded, but dropped out of the funding list in 1995 or 1996. Finally, the last dummy variable indicates villages funded in 1993 or 1994 despite the village selection rules suggesting no funding. Other types of errors are too rare to be included.

[29] Conditional logit model and Tobit model (with the censoring at zero and one) are conducted for equations (1) and (2), respectively. These non-linear specifications yield qualitatively consistent results.

4.2 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 utility of relatively poor and wealthy households. For simplicity, I call them the poor and non-poor.[30] First, the effect of inequality is unclear. On one hand, inequality can increase the gap in the marginal utility levels between the poor and non-poor 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 relative weight on the utility in favor of the non-poor. In addition, the relative importance of these factors could change if benefits provided to the poor empower them or leakage satiates the demand from the non-poor. This issue is explored using two indicators of inequality in consumption and education levels: the coefficient of variation of the predicted PCE[31] and education Gini index.[32]

Second, the human capital of village heads and administrative capability of village government can enhance better targeting if they are correlated with relatively equal weights on the utilities of the poor and non-poor and more accurate information on the marginal utility from receiving an IDT loan. The human capital of village heads is measured by their educational attainment conditional on their cohort,[33] and the technical competency of village government,

[30]The discussion in this section follows the model used in Galasso and Ravallion (2005).

[31]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 are likely to create the attenuation bias. This strengthens the view that, if significant differences are observed across villages, they are 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 the 1993 PODES or IDT administrative data.

[32]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 1[C] for the summary statistics of village characteristics).

[33]Younger village heads are more likely to have completed higher levels of education. In order to separate

LKMD, is measured by their self-reported capacity.[34] Measures are also included for the pre-existence of social organizations such as groups of farmers, health/nutrition advisors, and agricultural extension workers.

Third, the marginal utility from receiving IDT loans is likely to be higher if returns to investment are higher and the pre-existing supply of credit is scarce. These conditions may also reduce the gap in the marginal utility levels among the poor and non-poor. 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 non-poor is prioritized. This issue is assessed using the across-village variation in per household grant size. This variation arises because the same value of lump-sum grant was given to all selected villages regardless of population size. Thus, while controlling for different funding history, I am able to estimate the correlation between the budget size and targeting performance.[35]

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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.

[34] 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 (1) does not exist, (2) only exists in very basic form, (3) exists and is able to develop and conduct work projects utilizing grants from the central government matched with contributions of community members, or (4) 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 (3) or (4) as a village with relative technical competence. Since the form of LKMD originally developed in Java and was later put in place in other regions, I allow the correlation with targeting performance to vary in and outside Java.

[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.

5 Results on Overall Targeting Performance

The average degree of targeting[36] indicates that an increase in the relative poverty level is associated with a 6.4 (5.8) percent lower probability of being eligible for (participating in) IDT (Table 1), confirming the results found in Fig.3. It is also correlated with a Rp.27,796 smaller loan size.[37] The mean concentration measures suggest that 24 percent and 45 percent of benefits/beneficiaries accrue to the bottom first and second quintiles (Appendix Table 1[A]). Compared to universal allocation, therefore, the within-village distribution contributes to concentrating benefits to relatively poor households by 20% and 13%.

Among the list of village characteristics, the major correlates of better targeting are the average level of predicted PCE and its inequality. First, as the average PCE increases by one standard deviation (Rp.10,375), a marginally poorer household is 0.01 percent more likely to be eligible as well as to be participating. The household also receives Rp.7,470 larger benefits unconditional on loan receipt (Table 1). These changes amount to 18-27% of the average degree of targeting. Consistently, a marginal decrease in the average PCE is associated with a decline of 0.3-0.4 percent in the share of benefits accruing to relatively poor households (Table 2). 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 the households eligible and 6 percent had all the households receiving a loan. The equivalent figures are 4 percent and 3 percent among the relatively wealthy half of the villages.

Second, one standard deviation increase in the coefficient of variation in the predicted PCE

[36] This is computed as $\beta_0^H + \beta_1^H * \bar{V} + \beta_2^H * \bar{D}$, shown in the first row, based on the estimates for β_0^H (in the second row) and for β_1^H and β_2^H (in the rest of the rows) in Eq.(1).

[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 heads, many more members, higher shares of women and children, and housing made of inferior materials. Households headed by older males are more likely to receive larger loans (Appendix Table 3).

is accompanied by a 0.02 percent increase in the degree of targeting in terms of eligibility and participation and a Rp. 6,804 increase in terms of the unconditional loan value. This is equivalent to a 19-26% improvement relative to the average degree of targeting (Table 1). Interestingly, the results in Table 2 suggest that it is households in the second, and not the first, quintile who benefited the most from greater inequality. One standard deviation increase in the inequality measure is associated with a 1.3 percent larger share of benefits for the poorest group, which is positive, yet only half of the 2.6 percent increase for the second poorest. These results suggest that the 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, which could be more difficult in more equal villages. On the other hand, the poorest group is more likely to be included in beneficiaries regardless of the level of within-village inequality.

Though information on wealth inequality is unavailable in the SUSENAS, the results on inequality in educational attainment suggest a similar tendency: unequal villages exhibit better targeting in terms of the unconditional loan value (Table 1), which mainly benefits households in the second bottom quintile (Table 2). Altogether, these results suggest that ease of identifying the poor and justifying their needs could possibly overwhelm the larger political influence of local elites in more unequal communities.[38] These findings on the levels of poverty and inequality are consistent with the cross-country study by Coady et al. (2004).[39]

These results, which are not in line with previous anecdotal evidence, might reflect Indone-

[38]These results also provide an indication that consideration of profitability is unlikely to be a major cause of poor targeting. For if this was the case, inequality in education, which could be correlated with inequality in creditworthiness and entrepreneurship, should be associated with poorer targeting.

[39]Similar results are obtained when alternative inequality measures are used, such as Gini coefficient and the share of the top 20% of the predicted PCE distribution. This finding contrasts with Galasso and Ravallion (2005), who find a negative association between targeting and inequality in landholding. However, their definition of the poor (based on the national poverty level) makes it difficult to directly compare the two sets of results.

sia's political context. In the Suharto regime, village heads had incentives to look to upper-level government because they needed district-level government approval to run for village election, and were held accountable to the sub-district government once elected.[40] Properly executing national programs was one way to show their capability and loyalty to the members of this upper-level government (Antlov, 1995; Husken, 1994). For example, Antlov (1995) reports that a village leader tried to increase participation in a literacy program to make him look competent to sub-district officials. Under IDT, the list of participants was reported to the upper-level government, which in turn submitted the information 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, the level of self-reported administrative capacity of village government is not correlated with the targeting outcomes. Also, no clear performance gap is found among villages headed by persons with different age and education levels. Though the results indicate a significant gap among the younger cohort of village heads between the educated and less educated, neither of them exhibit a significant difference compared to the omitted group of village heads aged 48 and above who have not completed junior high school.

The other village characteristics show an association with targeting performance based on only one of the two specifications, most likely reflecting the methodological differences described in Appendix 1. For example, the household-level analysis indicates that better targeting is found in villages with a larger budget per household and previous program receipt, while villages dropped out of the funding list show worse targeting (Table 1). On the other

[40] The effectiveness of top-down monitoring in Indonesia is also shown in Olken (2007).

hand, only the village-level analysis results suggest that better targeting is found in villages with public transportation and a post office, while worse performance is observed in places with banks and agricultural/health advisors (Table 2).[41] Other characteristics such as density and past experience of shocks do not exhibit a significant association with targeting.[42]

6 Changes in Targeting Performance

6.1 Yearly Benefits

Thus far, the analysis has focused on the allocation of cumulative benefits. This section investigates changes in the yearly benefit distribution, and their association with initial conditions. In order to do this, the household-level specification is modified as follows:

$$\begin{aligned} Y_{ijt} &= \alpha_0^H + \beta_0^H X_{ijt} + \gamma_0^H [X_{ijt} * 1\{1995\}] + \delta_0^H [X_{ijt} * 1\{1996\}] \\ &\quad + \beta_1^H [X_{ijt} * V_j] + \gamma_1^H [X_{ijt} * V_j * 1\{1995\}] + \delta_1^H [X_{ijt} * V_j * 1\{1996\}] \\ &\quad + \beta_2^H [X_{ijt} * D_j] + \gamma_2^H [X_{ijt} * D_j * 1\{1995\}] + \delta_2^H [X_{ijt} * D_j * 1\{1996\}] \\ &\quad + \mu_j^H + \epsilon_{ijt}^H \end{aligned} \tag{3}$$

Parameters γ_0^H and δ_0^H show whether there are common yearly changes in the degree of targeting from the benchmark year, 1994. Key parameters γ_1^H and δ_1^H test for the similar

[41] Though the village-level analysis uses a subset of villages where at least one household is participating in the village-level analysis, the differences in the results are not due to the differences in the sample. Using the sample of villages that are used in the village-level analysis does not change the substantive results based on the household-level analysis (See Appendix 2).

[42] 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.

changes particularly for villages with characteristics indicated by V_j. With the village-level fixed effects and the controls for village selection, D_j, these parameters are identified from the changes within villages, not from the compositional changes in the sample.[43] The village-level analysis is similarly adjusted to incorporate the time dimensions:

$$Y_{jt} = \alpha_0^V + \gamma_1^V[V_j * 1\{1995\}] + \delta_1^V[V_j * 1\{1996\}] + \gamma_2^V[D_j * 1\{1995\}] + \delta_2^V[D_j * 1\{1996\}] + \mu_j^V + \epsilon_{jt}^V \quad (4)$$

Now the village-level analysis also includes the village-level fixed effects. Thus, the correlation between the outcome and village characteristics in the base year (1994) cannot be estimated. Parameters of interest, γ_1^V and γ_2^V, indicate whether changes in the concentration of program resources are correlated with initial local conditions. The error term is allowed to have the village-level clustering.[44]

6.2 Results on Changes in Targeting Performance

The results of estimating Eq.(3) confirm that the average degree of targeting declined (Table 3).[45] In 1994, a marginally poor household was 3 percent more likely to be a beneficiary and expected to receive Rp.9,384 (Column 1). These figures fell to 2 percent and Rp.5,285 in 1995, and 1 percent and Rp. 2,179 in 1996 (Columns 2-3). Though inaccurately estimated, the year effects estimated in Eq.(4) consistently indicate declines in the shares of beneficiaries

[43] In addition, in order to control for possible differences in the outcomes between the two survey years, I include the dummy variable indicating households observed in 1997, as well as its interaction with the relative poverty level. The results show that households in 1997 are more likely to receive benefits and achieve better targeting.

[44] Conditional logit estimation of Eq. (3) and Tobit estimation of Eq. (4) with provincial dummies result in qualitatively same conclusions. The within estimator and first-difference estimator for Eq.(4) also yield consistent results.

[45] The average degree of targeting for the benchmark year is calculated as $\beta_0^H + \beta_1^H * \bar{V} + \beta_2^H * \bar{D}$, its change between 1994 and 1995 (1994 and 1996) as $\gamma_0^H + \gamma_1^H * \bar{V} + \gamma_2^H * \bar{D}(\delta_0^H + \delta_1^H * \bar{V} + \delta_2^H * \bar{D})$.

and benefits accruing to relatively poor households (Table 4). The results also confirm greater reductions for the poorest quintile.

One of the main findings is that the deterioration in targeting was not concentrated in wealthier or unequal villages. Higher levels of average PCE and inequality in the PCE are correlated with better targeting of relatively poor households in 1994, and this advantage does not change over time (Table 3). The village-level analysis results consistently indicate the lack of changes in the association between targeting and the levels of poverty and inequality.

Contrastingly, targeting relatively deteriorates in villages with higher human capital of village heads (Table 3). That is, villages with young and educated heads provided more loan opportunities to the relatively poor in 1994, even compared to the omitted group. However, this advantage disappeared in 1995 and 1996. The village-level analysis suggests consistent changes between 1994 and 1995 (Table 4). It also reveals that the share of benefits declines particularly for the bottom quintile. These results suggest that overall within-village targeting declined because the successful performance, associated with young and educated village heads, did not last.

These results are likely to reflect the fact that monitoring of loan allocations became more difficult for village heads in later years - once eligible households were selected, community groups, not village heads, became responsible for loan management. Thus, young and educated heads may have played a role in ensuring eligibility for the poorest, but not in continuously providing loan opportunities to them. While the mechanism through which these heads demonstrate this temporary achievement is unclear from the empirical results, Indonesia's historical context provides one possible explanation. As discussed above, village heads had incentives to build a reputation as good implementers of national programs. Among them, young and educated heads often replaced traditional, inward-looking village heads in the 1980s, and were particularly loyal to the central government (Antlov, 1995; Husken, 1994). This historical background suggests the results reflect the stronger loyalty and administration skills of young and educated heads. On the other hand, it is also possible that they simply had a stronger preference for a more democratic selection.[46] The results do not allow determination of the specific pathways through which the age and education levels of village heads affect targeting performance.

Similar results are found for village government in Java with self-reported administrative competency (Table 3). These village governments better target their own poor in the initial year, but this advantage dissipates towards the end of the program period.[47] However, the village-level analysis results do not show a consistent pattern.

Finally, the household-level analysis indicates that a larger budget is associated with a higher degree of targeting, but the degree does not improve as additional funding is provided (Tables 3).[48] The overall positive relationship is consistent with the previous findings (Lanjouw and Ravallion, 1999). However, the lack of change in the relationship indicates that the effect of a budget cut and a budget increase may not be the same (Ravallion, 1999). The results for other variables (not reported) suggest that villages included for funding in 1995 and 1996 had poor targeting performance for the years in which they were not yet funded (as no one is a beneficiary). Once they became funded, however, they target better than the average. On the other hand, villages that dropped out of the funding list worsened targeting performance in the last year of the program period, possibly reflecting capture, but also the overall decline

[46] Rao and Ibanez (2003) discuss "benevolent capture," in which influential individuals dominate community-level decision-making, but consider the best interests of the community.

[47] The fact that this positive association between targeting and administrative capability is found only in Java might be because among the villages defined as "capable" in Java, a larger fraction is categorized in the most organized group.

[48] Note that, with the controls for funding history, the estimates for each year reflect the relative budget size among funded villages. Therefore, the lack of change in the degree of targeting suggests that it does not depend on the range of grant values for which the yearly estimates are obtained.

in the number of beneficiaries. Other initial conditions provide little significant, systematic association with targeting.[49]

7 Conclusions

Given the growing popularity in community-based development and resource allocation, the ability for poor communities to implement social programs has never been more critical. This paper has investigated the initial local conditions associated with community-based targeting performance using Indonesia's anti-poverty program, IDT. Using the rich information on pre-program conditions, I have shown that wealthier and more unequal villages tend to provide more resources to relatively poor households within the village. Exploiting the panel data on targeting performance, I have also demonstrated that wealthier and unequal villages constantly target well. 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 possibly larger political influence of local elites. I also find that young and educated heads are more likely to achieve better targeting, though only in the initial year. This is likely to have contributed to the better initial overall targeting and the deterioration afterwards.

The lack of the evidence for elite capture may look inconsistent with the previous anecdotal evidence. However, recent empirical studies do not always find a negative relationship between targeting and inequality (Bardhan and Mookherjee, 2006; Coady et al., 2004). Hence, my findings, in light of the previous research, suggest that the relationship between inequality and targeting might also be specific to local and program contexts. The nature of IDT benefits

[49] For instance, only the village-level analysis results indicate that villages with land access to outside village improve concentrating benefits to the second bottom quintiles. Density is associated with a temporary deterioration of targeting, while the fraction of educated heads and the pre-existence of a farmers' association are correlated with a temporary improvement.

(loans) as a private good might be attributable to the positive relationship between inequality and targeting (Bardhan and Mookherjee, 2006).[50] Indonesia's political context suggests that village leaders, particularly young, educated ones, had incentives to follow the national guideline of targeting the poor.

The disappearance of the initially positive correlation between targeting and young, educated heads is likely to reflect the fact that, once eligibility was allocated, community groups became responsible for actual loan management. This suggests that possible gain from more loyal or benevolent local agents could be tapered without continued monitoring of benefit allocations by them. These findings in turn give rise to questions such as whether community-based targeting could generally be improved by training village heads and officials, modifying program design and instructions, and strengthening monitoring by upper-level government and local agents.[51] Establishing empirical evidence on these issues from a broad range of settings is likely to enhance utilization of local knowledge and implementation of community-based social programs.

[50] 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).

[51] 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.

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Figure 1: Distribution of overall IDT beneficiaries and benefits by decile of predicted per capita expenditure (PCE) (1997, Rural Indonesian villages)

Fig.1A: Share of beneficiaries

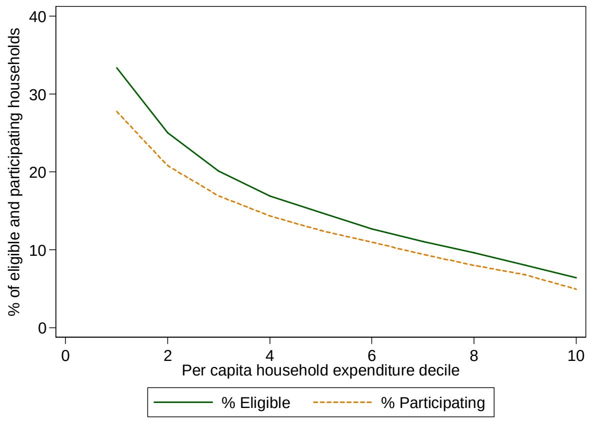


Fig.1B: Average loan size

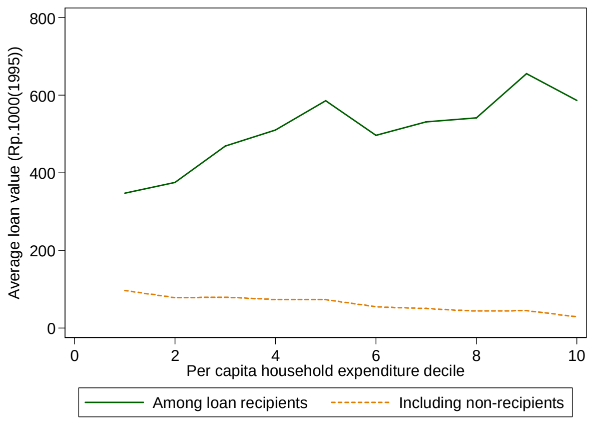
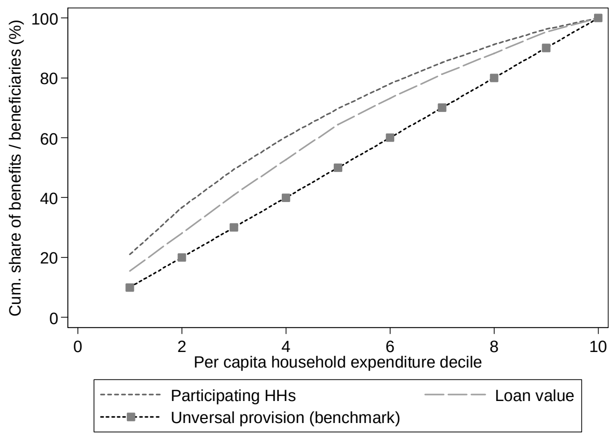


Fig.1C: Concentration curves for participants and loan money



Sources: 1997 SUSENAS and IDT data.

Notes:

- Households are divided into deciles based on the predicted real household per capita expenditure (PCE). See Section 3 for details of the prediction procedure. PCE and loan size are in terms of 1995 Jakarta prices.
- Participating households are defined as households having received an IDT loan at least once.
- Loan size is the cumulative amount of money lent to a household over the program period.
- In Fig.1B, the loan value for non-recipients is assumed to be zero.
- Fig.1C shows the cumulative share of participating households (beneficiaries) with different levels of predicted PCE as well as the share of loan money (benefits) accruing to households with different levels of predicted PCE. The straight line indicates the allocation that would be realized under universal provision.

Figure 2: Decomposition of inter- and intra-village distribution of IDT beneficiaries and benefits by decile of predicted PCE (1997, Rural Indonesian villages)

Fig.2A: Share of potential and actual beneficiaries

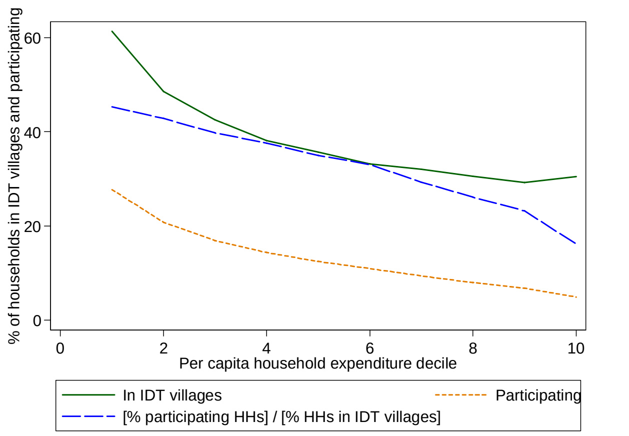


Fig.2B: Potential and actual benefit (loan) size

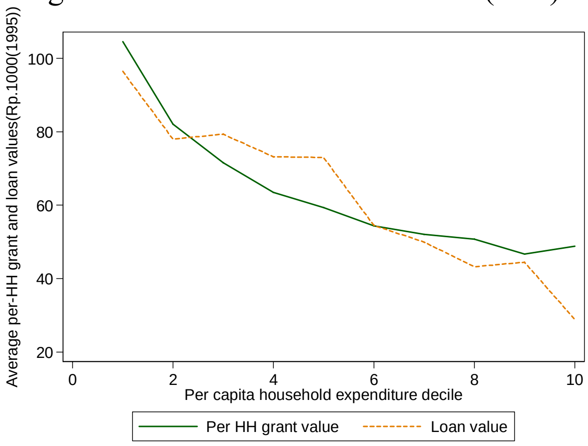
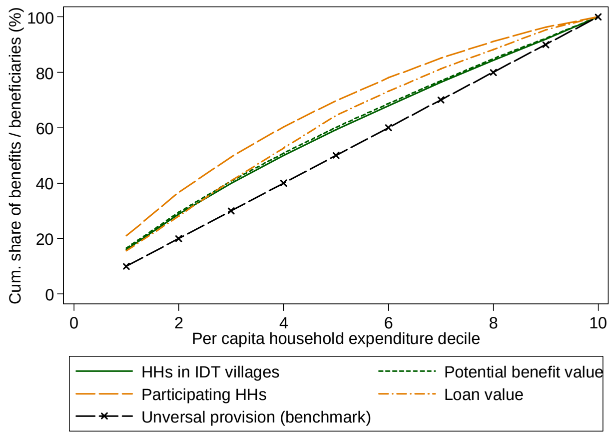


Fig.2C: Concentration curves of potential and actual beneficiaries/benefits



Sources: 1997 SUSENAS and IDT data.

Notes:

- See the notes for Figure 1 for the definitions of predicted household PCE, participation, and loan size.
- In Fig.2A, potential beneficiaries are defined as households (including non-participants) living in villages that were funded at least once. The distribution of potential beneficiaries depends only on the inter-village targeting. On the other hand, the distribution of actual beneficiaries depends on inter- and intra-village selection.
- Similarly, in Fig.2B, potential benefit size is defined as the per household grant value. The distribution of this value reflects the inter-village targeting. On the other hand, the distribution of the average loan size shows the combined effects of the selection of villages and the within-village allocation of loan money.

Figure 3: Within-village distribution of IDT beneficiaries and benefits by quintile of standardized predicted PCE (1996 and 1997, Rural Indonesian villages funded at least once in IDT)

Fig.3A: Share of beneficiaries

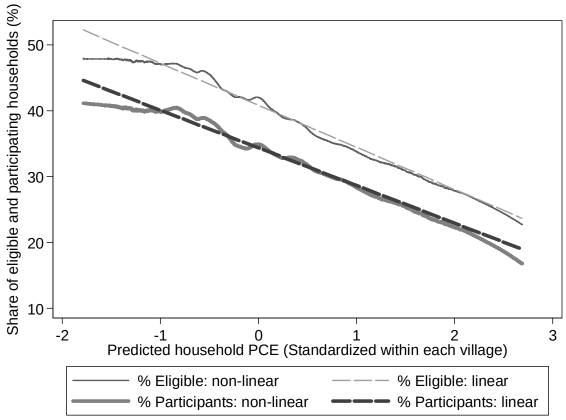


Fig.3B: Average loan size

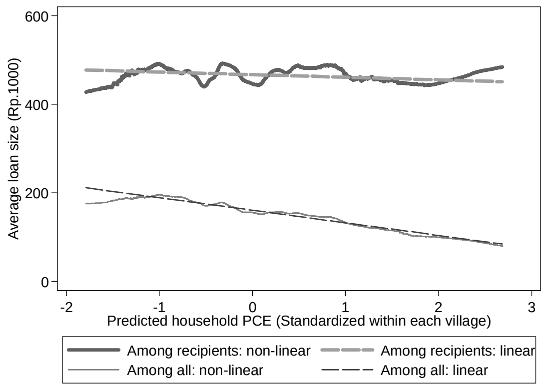


Fig.3C: Within-village concentration curves for
concentration
beneficiaries and benefits

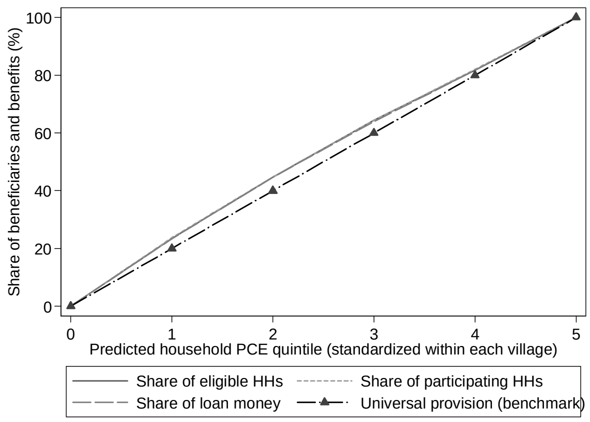
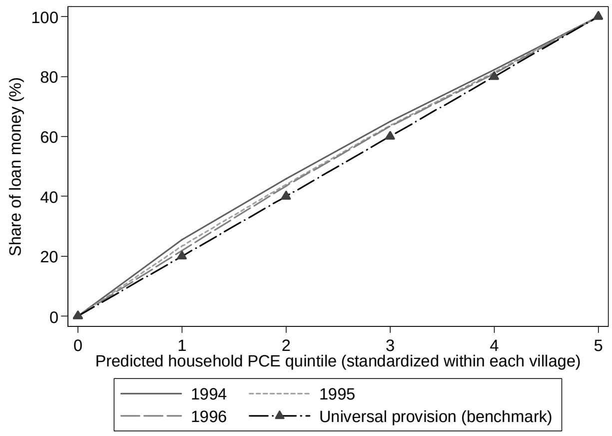


Fig.3D: Changes in within-village

of benefits



Sources: 1996 and 1997 SUSENAS and IDT data.
Notes:

- Fig.3A depicts the non-parametric relationship between the share of households in targeted villages that became eligible for an IDT loan by 1997 and the predicted, standardized household PCE. It also indicates the relationship between the share of households that received an IDT loan by 1997 and the predicted standardized household PCE. The non-parametric estimation is based on STATA's lowess procedure. The straight lines indicate the OLS fitted values.
- Similarly, Fig.3B shows linear and non-parametric relationships for the total loan value received under IDT with and without including non-participants as zeros.
- Fig.3C shows the cumulative shares of eligible households and participating households that are from each of the quintiles defined by the predicted standardized household PCE. It also shows the cumulative share of loan money accruing to households with the predicted standardized PCE falling in each of the quintiles.
- Fig.3D depicts the concentration curve for annual benefits. The share of beneficiaries shows the same pattern of changes.

Table 1: Heterogeneity by village characteristics in the relationship between predicted, standardized household PCE and IDT eligibility, participation, and loan size (1997, Rural Indonesia)
Household-level analysis based on the village-level fixed effects model

	(1)	(2)	(3)	(4)	(5)
	Eligibility	Participation	Participation given eligibility	Loan size given participation	Loan size including zeros
Average degree of targeting	-0.064	-0.058	-0.009	-0.944	-27.796
P-value	0.000	0.000	0.002	0.867	0.000
Predicted standardized household PCE	0.085	0.078	0.019	53.979	104.639
	[0.022]**	[0.021]**	[0.025]	[49.922]	[26.632]**
The interaction between the predicted household PCE and:	-0.0104	-0.0104	0.1798		-7.4700
Village-level average predicted PCE (1,000 rupiah, 1995 Jakarta prices)	-0.001	-0.001	0	-0.591	-0.72
	[0.000]**	[0.000]**	[0.000]	[0.814]	[0.332]*
Village-level coefficient of variation in the predicted PCE	-0.174	-0.165	-0.032	-77.962	-73.607
	[0.025]**	[0.024]**	[0.030]	[52.136]	[23.260]**
Budget size (Total (1994-96) per household grant value in the village)	-0.001	-0.001	0	-0.317	-1.422
	[0.000]**	[0.000]**	[0.000]	[0.471]	[0.345]**
Density (100 persons per hectare)	-0.029	-0.055	-0.15	105.213	6.397
	[0.040]	[0.041]	[0.079]	[117.047]	[22.414]
Share of household heads in the village who completed primary education or above	-0.018	-0.012	-0.006	2.498	-8.188
	[0.011]	[0.011]	[0.011]	[30.921]	[13.668]
Village level education Gini index	-0.007	0.002	0.006	-31.102	-33.017
	[0.013]	[0.013]	[0.012]	[32.874]	[13.759]*
1{village head is aged 39 or less}	0.012	0.012	0.007	7.672	-3.74
	[0.007]	[0.007]	[0.008]	[18.853]	[9.713]
1{village head is aged 39 or less and completed high school or higher education}	-0.019	-0.014	0.004	-0.815	2.161
	[0.007]**	[0.007]*	[0.007]	[20.014]	[9.946]
1{village head is aged between 40 and 47}	-0.002	0.004	0.011	8.061	7.487
	[0.007]	[0.007]	[0.007]	[20.853]	[9.083]
1{village head is aged between 40 and 47 and completed junior high school or higher education}	-0.003	-0.001	-0.001	10.219	-9.147
	[0.007]	[0.007]	[0.007]	[16.009]	[8.000]
1{village head is aged 48 and above and completed junior high school or higher education}	-0.005	-0.005	-0.004	13.388	-6.312
	[0.007]	[0.007]	[0.008]	[21.681]	[8.503]
1{village head is female}	-0.002	0.003	-0.004	18.264	1.405
	[0.018]	[0.016]	[0.011]	[26.284]	[8.332]
1{village government (LKMD) is established} * 1{Outside of Java}	-0.004	-0.005	-0.002	0.627	-16.535
	[0.005]	[0.005]	[0.006]	[15.530]	[7.781]*
1{village government (LKMD) is established} * 1{Java}	-0.012	-0.017	-0.02	58.219	5.202
	[0.012]	[0.011]	[0.014]	[49.558]	[18.040]
1{village has farmers' associations}	-0.001	-0.005	-0.009	-6.459	-1.743
	[0.005]	[0.005]	[0.005]	[12.320]	[6.043]
1{village has groups of advisors such as agricultural extension and health and nutrition}	0.005	0.004	-0.002	16.89	4.77
	[0.005]	[0.005]	[0.004]	[11.827]	[6.525]
1{village has at least one cooperative}	0.005	0.001	-0.007	-14.112	-4.248
	[0.005]	[0.005]	[0.008]	[10.340]	[5.912]
1{village has at least one bank}	-0.01	-0.005	0.012	9.548	4.865
	[0.006]	[0.006]	[0.009]	[16.340]	[5.847]
1{village received at least one credit program in the previous year}	-0.013	-0.01	0.01	7.295	-0.956
	[0.005]*	[0.005]*	[0.006]	[12.767]	[5.922]

1{village's main access is through land}	-0.009	-0.007	0.003	-11.304	-19.941
	[0.007]	[0.007]	[0.007]	[21.740]	[11.663]
1{village's main access is through land and the inter-village road is made of asphalt or hardened}	0.008	0.005	-0.007	19.999	13.452
	[0.005]	[0.005]	[0.006]	[11.636]	[5.720]*
1{village has access to public transportation within the village}	0.002	0.005	0.006	3.832	5.447
	[0.004]	[0.004]	[0.005]	[10.448]	[5.274]
1{village has a public television}	-0.001	-0.004	-0.008	7.764	4.584
	[0.005]	[0.005]	[0.006]	[15.467]	[5.901]
1{village has a post office}	0.003	-0.003	-0.02	-6.327	-7.165
	[0.008]	[0.008]	[0.017]	[18.746]	[5.519]
1{village experienced natural disasters such as droughts, floods, earthquakes and volcano eruptions at least once in the past three years}	-0.002	-0.004	-0.008	-0.967	5.355
	[0.005]	[0.004]	[0.005]	[12.338]	[5.604]
1{village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year}	-0.005	0	0.011	-11.669	-5.659
	[0.005]	[0.005]	[0.006]	[11.527]	[6.298]
1{village's grant status in 1993 depends on field officers' subjective perceptions}	-0.013	-0.01	0.001	3.507	-0.081
	[0.006]	[0.006]	[0.007]	[17.305]	[9.388]
1{village is newly added to the treatment group in 1995}	-0.021	-0.009	0.005	11.655	7.485
	[0.010]*	[0.009]	[0.011]	[31.024]	[15.339]
1{village is newly added to the treatment group in 1996}	-0.001	0.011	0.002	0.107	-0.233
	[0.011]	[0.010]	[0.013]	[27.666]	[13.729]
1{village was once funded, but dropped out of the treatment group in 1995 or 96}	0.035	0.032	0	-24.852	2.56
	[0.011]**	[0.011]**	[0.007]	[23.190]	[18.009]
Difference between the village score and the 1993 provincial threshold	0.008	0.005	-0.002	-10.396	2.633
	[0.003]*	[0.003]	[0.004]	[9.293]	[3.268]
Difference between the village score and the 1994 provincial threshold	-0.003	0.001	0.005	-0.902	-3.571
	[0.002]	[0.002]	[0.003]	[6.176]	[2.630]
1{village was funded in 1993 or 1994 despite the rules suggesting no funding}	0.006	-0.004	-0.023	24.545	-26.441
	[0.018]	[0.017]	[0.018]	[43.208]	[20.817]
1{Sumatera}	0.013	-0.006	-0.008	13.42	-19.763
	[0.009]	[0.009]	[0.009]	[21.934]	[11.316]
1{Java}	0.02	0.004	0.007	-90.627	-30.893
	[0.015]	[0.015]	[0.019]	[57.907]	[21.651]
1{Nusa Tenggera}	-0.011	-0.015	-0.009	9.647	-9.867
	[0.010]	[0.009]	[0.010]	[19.030]	[8.769]
1{Kalimantan}	0.01	-0.002	-0.008	-37.389	-56.246
	[0.010]	[0.010]	[0.013]	[42.647]	[17.948]**
1{Sulawesi}	-0.01	-0.02	0.006	-26.143	-18.548
	[0.011]	[0.010]*	[0.011]	[20.389]	[10.346]
Observations	46836	46836	19091	16048	46836
Villages	2832	2832	2382	2241	2832
F-stat	28.14	24.66	0.97	0.86	5.58

Sources: 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.
Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.
2. See the Notes for Appendix Table 1 for the definition of the outcome and explanatory variables.
3. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 Jakarta prices.
4. All the regression equations include five dummy variables indicating regions (Sumatera, Java, Nusa Tenggera, Kalimantan, and Sulawesi).
5. Predicted household PCE is based on the pre-program 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.

Table 2: Village characteristics associated with the shares of overall beneficiaries and benefits found in the bottom one and two quintiles of predicted household PCE (1997, Rural Indonesia)
Village-level analysis based on the province-level fixed effects model

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of eligible households whose PCE is below:		Share of participating households whose PCE is below:		Share of loan money provided to households whose PCE is below:	
	20th pctile	40th pctile	20th pctile	40th pctile	20th pctile	40th pctile
	0.013	0.026	0.008	0.020	0.009	0.019
Village-level average predicted PCE	0.004	0.004	0.003	0.003	0.003	0.003
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Village-level coefficient of variation in the predicted PCE	0.139	0.28	0.082	0.221	0.095	0.209
	[0.050]**	[0.059]**	[0.056]	[0.066]**	[0.059]	[0.070]**
Budget size (Total (1994-96) per household grant value in the village)	0	0	-0.001	-0.001	-0.001	-0.001
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]
Density (100 persons per hectare)	-0.081	-0.043	-0.052	-0.062	-0.032	-0.076
	[0.090]	[0.105]	[0.099]	[0.116]	[0.104]	[0.123]
Share of household heads in the village who completed primary education or above	-0.041	0.01	-0.036	0.044	-0.033	0.037
	[0.023]	[0.027]	[0.026]	[0.030]	[0.027]	[0.032]
Village level education Gini index	-0.01	0.065	-0.009	0.08	0.004	0.083
	[0.029]	[0.034]	[0.032]	[0.038]*	[0.034]	[0.040]*
1{village head is aged 39 or less}	-0.025	-0.03	-0.027	-0.034	-0.024	-0.032
	[0.013]	[0.015]	[0.014]	[0.017]*	[0.015]	[0.018]
1{village head is aged 39 or less and completed high school or higher education}	0.038	0.042	0.034	0.046	0.034	0.05
	[0.015]*	[0.017]*	[0.016]*	[0.019]*	[0.017]*	[0.020]*
1{village head is aged between 40 and 47}	-0.006	0.011	-0.011	0.01	-0.01	0.008
	[0.013]	[0.016]	[0.015]	[0.018]	[0.016]	[0.019]
1{village head is aged between 40 and 47 and completed junior high school or higher education}	-0.002	0.011	-0.009	0.002	-0.001	0.012
	[0.015]	[0.017]	[0.016]	[0.019]	[0.017]	[0.020]
1{village head is aged 48 and above and completed junior high school or higher education}	-0.02	0.004	-0.023	0.008	-0.021	0.019
	[0.014]	[0.016]	[0.016]	[0.018]	[0.016]	[0.019]
1{village head is female}	-0.022	0.022	-0.036	0.013	-0.037	0.015
	[0.032]	[0.038]	[0.036]	[0.043]	[0.038]	[0.045]
1{village government (LKMD) is established} * 1{Outside of Java}	-0.007	-0.012	-0.005	-0.007	0	-0.009
	[0.011]	[0.013]	[0.012]	[0.014]	[0.013]	[0.015]
1{village government (LKMD) is established} * 1{Java}	-0.019	-0.037	-0.014	-0.044	-0.032	-0.062
	[0.034]	[0.040]	[0.037]	[0.044]	[0.039]	[0.046]
1{village has farmers' associations}	0.001	0.009	0.006	0.013	0.003	0.013
	[0.009]	[0.011]	[0.010]	[0.012]	[0.011]	[0.013]
1{village has groups of advisors such as agricultural extension and health and nutrition}	-0.01	-0.018	-0.021	-0.022	-0.024	-0.029
	[0.009]	[0.011]	[0.010]*	[0.012]	[0.011]*	[0.013]*
1{village has at least one cooperative}	0.007	-0.008	0.008	-0.004	0.018	0.008
	[0.011]	[0.013]	[0.013]	[0.015]	[0.013]	[0.016]
1{village has at least one bank}	-0.021	-0.026	-0.037	-0.04	-0.031	-0.034
	[0.014]	[0.016]	[0.015]*	[0.018]*	[0.016]	[0.019]
1{village received at least one credit program in the previous year}	0.014	0.013	0.005	0.004	0.004	0.001

	[0.010]	[0.012]	[0.011]	[0.013]	[0.012]	[0.014]
1{village's main access is through land}	0.03	0.019	0.026	0.025	0.032	0.024
	[0.015]*	[0.017]	[0.017]	[0.020]	[0.018]	[0.021]
1{village's main access is through land and the inter-village road is made of asphalt or hardened}	-0.017	-0.018	-0.019	-0.021	-0.024	-0.03
	[0.010]	[0.011]	[0.011]	[0.013]	[0.011]*	[0.013]*
1{village has access to public transportation within the village}	0.011	0.021	0.014	0.028	0.01	0.02
	[0.009]	[0.011]*	[0.010]	[0.012]*	[0.011]	[0.013]
1{village has a public television}	0.01	0.018	0.005	0.021	0.003	0.015
	[0.010]	[0.012]	[0.011]	[0.013]	[0.012]	[0.014]
1{village has a post office}	-0.017	0.049	-0.002	0.053	0.003	0.06
	[0.019]	[0.022]*	[0.021]	[0.025]*	[0.022]	[0.026]*
1{village experienced natural disasters such as droughts, floods, earthquakes and volcano	-0.004	-0.007	0.014	0.003	0.018	0.003
eruptions at least once in the past three years}	[0.009]	[0.010]	[0.010]	[0.012]	[0.010]	[0.012]
1{village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year}	0.004	0.012	-0.002	-0.005	-0.005	-0.008
	[0.010]	[0.012]	[0.011]	[0.013]	[0.012]	[0.014]
1{village's grant status in 1993 depends on field officers' subjective perceptions}	-0.008	0.025	-0.013	0.012	-0.012	0.016
	[0.013]	[0.016]	[0.015]	[0.017]	[0.016]	[0.018]
1{village is newly added to the treatment group in 1995}	-0.029	0.014	-0.033	0.002	-0.025	0.005
	[0.020]	[0.024]	[0.023]	[0.027]	[0.024]	[0.028]
1{village is newly added to the treatment group in 1996}	-0.002	0.024	-0.013	0.016	-0.007	0.032
	[0.022]	[0.025]	[0.025]	[0.029]	[0.026]	[0.031]
1{village was once funded, but dropped out of the treatment group in 1995 or 96}	-0.026	-0.015	-0.008	0.008	-0.01	0.002
	[0.022]	[0.025]	[0.024]	[0.028]	[0.025]	[0.030]
Difference between the village score and the 1993 provincial threshold	0.002	-0.006	0.006	-0.003	0.004	-0.004
	[0.007]	[0.009]	[0.008]	[0.010]	[0.009]	[0.010]
Difference between the village score and the 1994 provincial threshold	0.002	0.002	0.001	0	0	-0.001
	[0.006]	[0.007]	[0.006]	[0.008]	[0.007]	[0.008]
1{village was funded in 1993 or 1994 despite the rules suggesting no funding}	-0.037	-0.035	-0.036	-0.022	-0.031	-0.026
	[0.035]	[0.041]	[0.039]	[0.046]	[0.041]	[0.049]
Observations	2382	2382	2241	2241	2241	2241
F-stat	2.33	3.21	1.63	2.34	1.62	2.3
F(Prov FE)	2.37	1.94	1.88	1.56	1.91	1.65

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

Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.

2. See the Notes for Appendix Table 1 for the definition of the outcome and explanatory variables.

3. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 Jakarta prices.

4. The sample size is smaller than that in Table 1 because villages with at least one beneficiary are used in the village-level analysis.

Table 3: Changes in the heterogeneity by village characteristics in the relationship between predicted, standardized household PCE and IDT participation and loan size (1994-1996, Rural Indonesia)
Household-level analysis based on the village-level fixed effects model

	(1)	(2)	(3)	(4)	(5)	(6)
	Participation			Loan size including zeros		
	1994 benchmark	1994-95 deviation	1994-96 deviation	1994 benchmark	1994-95 deviation	1994-96 deviation
Average degree of targeting	-0.028	0.008	0.011	-9.384	4.100	7.205
P-value	0	0	0	0	0.0101	0.002
Year dummy		-0.015	0.012		-6.049	5.286
		[0.004]**	[0.006]*		[2.123]**	[4.463]
Predicted standardized household PCE	0.016	0.014	0.024	15.755	7.491	16.392
	[0.010]	[0.013]	[0.019]	[6.660]*	[9.208]	[14.523]
The interaction between the predicted household PCE and:						
Village-level average predicted PCE	0	0	0	-0.207	0.086	-0.103
	[0.000]**	[0.000]	[0.000]	[0.079]**	[0.135]	[0.220]
Village-level coefficient of variation in the predicted PCE	-0.08	0.023	0.004	-21.176	15.154	-5.434
	[0.013]**	[0.015]	[0.024]	[7.799]**	[10.743]	[14.763]
Budget size (Cumulative per household grant value in the village)	-0.001	0	0	-0.455	0.161	0.206
	[0.000]**	[0.000]	[0.000]	[0.208]*	[0.212]	[0.271]
Density (100 persons per hectare)	-0.008	0.01	0.02	-0.793	0.56	18.675
	[0.008]	[0.008]	[0.026]	[2.294]	[2.897]	[17.661]
Share of household heads in the village who completed primary education or above	-0.008	0.002	0	-3.038	-1.863	5.841
	[0.005]	[0.007]	[0.010]	[3.711]	[5.324]	[9.727]
Village level education Gini index	0	-0.002	0.021	-3.141	-9.052	8.819
	[0.007]	[0.008]	[0.012]	[3.378]	[5.694]	[8.942]
1{village head is aged 39 or less}	0.002	0	0.002	-1.608	-0.189	2.625
	[0.003]	[0.004]	[0.006]	[2.753]	[3.418]	[6.323]
1{village head is aged 39 or less and completed high school or higher education}	-0.009	0.01	0.005	0.101	1.974	-2.063
	[0.004]*	[0.004]*	[0.007]	[2.779]	[4.482]	[6.064]
1{village head is aged between 40 and 47}	0	0.004	-0.005	1.13	2.831	-7.583
	[0.003]	[0.004]	[0.006]	[2.640]	[3.491]	[6.642]
1{village head is aged between 40 and 47 and completed junior high school or higher education}	-0.002	-0.004	0.005	-0.731	-3.946	5.163
	[0.003]	[0.005]	[0.007]	[2.019]	[3.145]	[5.310]
1{village head is aged 48 and above and completed junior high school or higher education}	-0.001	-0.002	-0.006	-1.814	-0.473	-0.169
	[0.003]	[0.004]	[0.006]	[2.971]	[3.682]	[6.107]
1{village government (LKMD) is established} * 1{Outside of Java}	0.001	-0.002	0.003	-1.148	-2.372	-4.271
	[0.002]	[0.003]	[0.005]	[2.398]	[3.201]	[4.966]
1{village government (LKMD) is established} * 1{Java}	-0.017	0.003	0.024	-3.78	1.973	8.331
	[0.006]**	[0.008]	[0.012]*	[2.346]	[3.527]	[8.665]
Observations			238572			238572
Villages			4712			4712
F-stat			11.88			5.73

Sources: 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.
Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.
2. See the Notes for Appendix Table 1 for the definition of the outcome and explanatory variables.
3. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 Jakarta prices.
4. A selected set of estimates is shown. The regression equations include the same set of village characteristics as Table 1, interacted with the household relative poverty level and the year dummies.

Table 4: Changes in the association between village characteristics and the shares of beneficiaries and benefits found in the bottom four deciles of predicted household PCE (1994-1996, Rural Indonesia)
Village-level analysis based on the village-level fixed effects model

	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	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1994-95 deviation	1994-96 deviation	1994-95 deviation	1994-96 deviation	1994-95 deviation	1994-96 deviation	1994-95 deviation	1994-96 deviation
1{1994 per household grant value is greater than the median}	-0.004		-0.003		-0.003		-0.002	
	[0.002]		[0.002]		[0.002]		[0.002]	
Year dummy	-0.074	-0.142	-0.046	-0.139	0.053	-0.047	0.094	-0.008
	[0.078]	[0.117]	[0.083]	[0.119]	[0.089]	[0.138]	[0.093]	[0.141]
Village-level average predicted PCE	-0.001	0.002	-0.002	0.002	-0.001	0.003	-0.002	0.002
	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]
Village-level coefficient of variation in the predicted PCE	-0.02	-0.113	-0.041	-0.093	-0.199	-0.028	-0.183	0.017
	[0.103]	[0.156]	[0.105]	[0.161]	[0.119]	[0.180]	[0.123]	[0.188]
Budget size (Cumulative per household grant value in the village)	0.001	0.002	0.001	0.002	0.001	-0.001	0	-0.002
	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]
Density (100 persons per hectare)	-0.096	-0.108	-0.094	-0.071	-0.163	-0.145	-0.164	-0.123
	[0.047]*	[0.164]	[0.046]*	[0.171]	[0.043]**	[0.253]	[0.043]**	[0.275]
Share of household heads in the village who completed primary education or above	0.115	0.006	0.122	0.016	0.109	-0.031	0.101	-0.021
	[0.047]*	[0.069]	[0.048]*	[0.070]	[0.053]*	[0.080]	[0.055]	[0.081]
Village level education Gini index	-0.012	-0.086	-0.014	-0.08	0.018	-0.147	-0.003	-0.15
	[0.052]	[0.081]	[0.052]	[0.082]	[0.062]	[0.095]	[0.066]	[0.096]
1{village head is aged 39 or less}	0.031	0.068	0.033	0.06	-0.027	0.027	-0.023	0.024
	[0.029]	[0.040]	[0.030]	[0.041]	[0.032]	[0.046]	[0.033]	[0.047]
1{village head is aged 39 or less and completed high school or higher education}	-0.06	0.006	-0.072	0.003	-0.027	-0.015	-0.036	-0.022
	[0.029]*	[0.041]	[0.030]*	[0.042]	[0.033]	[0.049]	[0.034]	[0.050]
1{village head is aged between 40 and 47}	-0.003	0.034	-0.007	0.011	-0.04	-0.014	-0.037	-0.032
	[0.029]	[0.042]	[0.030]	[0.043]	[0.032]	[0.047]	[0.033]	[0.048]
1{village head is aged between 40 and 47 and completed junior high school or higher education}	0.002	-0.007	0	0.017	0.024	-0.01	0.021	0.011
	[0.030]	[0.041]	[0.031]	[0.041]	[0.036]	[0.050]	[0.037]	[0.051]
1{village head is aged 48 and above and completed junior high school or higher education}	-0.01	-0.009	-0.016	-0.011	-0.073	-0.026	-0.073	-0.023
	[0.033]	[0.046]	[0.034]	[0.047]	[0.035]*	[0.051]	[0.036]*	[0.053]
1{village government (LKMD) is established} * 1{Outside of Java}	-0.024	0.013	-0.024	0.027	0.006	-0.01	0.002	0
	[0.022]	[0.029]	[0.023]	[0.030]	[0.026]	[0.036]	[0.027]	[0.037]
1{village government (LKMD) is established} * 1{Java}	0.14	0.159	0.124	0.143	0.104	0.118	0.094	0.1
	[0.090]	[0.095]	[0.092]	[0.095]	[0.079]	[0.105]	[0.080]	[0.107]
Observations		5926		5926		5926		5926
F-stat		1.65		1.69		1.63		1.68
F(Prov FE)		3420		3420		3420		3420

Sources: 1996 and 1997 SUSENAS, 1993 PODES, and IDT data.
Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.
2. See the Notes for Appendix Table 1 for the definition of the outcome and explanatory variables.
3. All the loan and grant values as well as the PCE values are in terms of 1,000 rupiah, 1995 Jakarta prices.
4. A selected set of estimates 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. This is because, within each year, all the included (thus funded) villages take the value of one for these variables.

Appendix 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.

$$Y_{ij} = \alpha_0 + \beta_0 X_{ij} + \beta_1 [X_{ij} * V_j] + \mu_j + \epsilon_{ij} \tag{5}$$
$$Y_j = \alpha_0 + \beta_0 V_j + \epsilon_j \tag{6}$$

Suppose that the average allocation in village j is $y_j^1, , y_j^{Nj}$. If villages indicated by a dummy V_j deviate from this allocation by providing α to all households, the new allocation is $y_j^1 + \alpha, , y_j^{Nj} + \alpha$. 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 Eq.(5) as a significant change in targeting performance. Suppose that a dummy variable D_{ij} indicates relatively poor households, and a fraction s of the households are regarded as poor. Then, the concentration measure Y_j can be expressed as B_p/B where $B_p = \Sigma[y_{ij} * d_{ij}]$ and $B = \Sigma y_{ij}$. For villages indicated by V_j, the outcome variable is $(B'_p/B') = \Sigma[(y_{ij} + \alpha) * d_{ij}]/\Sigma(y_{ij} + \alpha)$. The deviation from the overall average is $(B_p/B) - (B'_p/B') = c * [B_p - sB]$ where $c = N_j * [\alpha/B] * B'$. 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, Table 2 shows that only the village-level analysis results show that a young and less educated village head is associated with worse targeting. This suggests that these villages allocate more benefits (of the same size) to both the relatively poor and wealthy compared to the overall performance, which results in deterioration of targeting measured by concentration. Villages that had a post office and public transportation are likely to provide less benefits of the same size to the relatively poor and wealthy; as a result they exhibit more concentration of benefits among the bottom 40% of households.

On the other hand, a proportional change in which $y'_{ij} = y_{ij}\gamma$ $(\gamma > 1)$ is regarded as neutral by the concentration measure. This change however is regarded as a deviation in Eq.(5). Suppose that the demeaned data is $y^*_{ij} = y_{ij} - \bar{y_j}$, and the degree of targeting for the baseline village $(V_j = 0)$ is $T = \Sigma x^*_{ij} y^*_{ij} / \Sigma x^{*2}_{ij}$. After the proportional change, $y^{*'}_{ij} = \gamma y^*_{ij}$. $T' = \Sigma x_{ij} * \gamma y^*_{ij} / \Sigma x^{*2}_{ij} = \gamma T$. Thus, if $T < 0$, a proportional change is regarded as an improvement in the village fixed model. For example, a larger budget is associated with better targeting only in the household-level analysis (Table 1). This suggests that villages with a larger budget attain a larger within-village gap in the probability of being a beneficiary between relatively poor and wealthy households; however, the increments are proportional to the probabilities attained by these households in villages with a smaller budget, and thus not detected by the village-level analysis as targeting-improving.

Appendix 2: The difference in the sample

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 they 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, yet does not affect targeting performance. Instead of doing the selection correction, the household-level analysis results are examined based on villages included in the village-level analysis. The results are substantively consistent.

Appendix Table 1[A]: Summary statistics of outcome variables for rural Indonesia (1997)

Household-level outcomes	Obs.	Mean	SD
1 if a household is eligible (someone is a member of an IDT community group)	46836	0.408	0.491
1 if a household has someone participating in IDT (receiving a loan)	46836	0.343	0.475
Cumulative loan value among participants (Rp.1,000 (1995))	16048	468	972
Cumulative loan value among all (Rp.1,000 (1995), including zeros)	46836	160	611

Village-level outcomes	Obs	Mean	SD
Share of eligible households whose PCE is less than the 20th percentile	2382	0.235	0.193
Share of eligible households whose PCE is less than the 40th percentile	2382	0.447	0.227
Share of participating households whose PCE is less than the 20th percentile	2241	0.237	0.208
Share of participating households whose PCE is less than the 40th percentile	2241	0.447	0.246
Share of loan money given to households whose PCE is less than the 20th percentile	2241	0.234	0.219
Share of loan money given to households whose PCE is less than the 40th percentile	2241	0.446	0.259

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

Notes:1. An eligible household has a member who belongs to a community group that was the unit of loan management under IDT.
2. A participating household has received at least one loan by January of 1997.
3. Cumulative loan value is the total amount of money extended as credit between the beginning of IDT and January of 1997.
4. The PCE is predicted based on the relationship between the actual PCE and household characteristics in 1993 and 1994 (see section 3). It is further standardized in each village. Thus, 20th and 40th percentile is measured within each village.

Appendix Table 1[B]: Summary statistics of household characteristics for rural Indonesia (1997)

Household chracteristics	Mean	SD
Per capita expenditure (PCE) per month (Rp.1,000 (1995))	46.95	26.72
Predicted PCE per month (Rp.1,000 (1995))	46.61	16.98
Characteristics of the household head		
Age	43.34	13.36
Age^2	2057	1279
1{Male}	0.894	0.308
1{Single}	0.026	0.158
1{Married}	0.854	0.353
Educational attainment:		
1{Attended but attained no degree}	0.293	0.455
1{Completed primary school}	0.304	0.460
1{Completed secondary school}	0.165	0.371
1{Can speak Indonesian}	0.826	0.379
1{Can read and write alphabet}	0.730	0.444
Housing quality		
Floor area (1000m^2)	0.053	0.039
1{Wall is made of inferior materials}	0.347	0.476
1{Roof is made of inferior materials}	0.304	0.460
1{Floor is made of inferior materials}	0.406	0.491
1{Inferior source of light is used}	0.520	0.500
1{No toilet facility}	0.420	0.494
Demographic characteristics		
Household size	4.38	1.93
Share of members aged 0-4	0.101	0.144
Share of members aged 5-15	0.241	0.215
Share of female members aged 16-55	0.281	0.172
Share of male members aged 16-55	0.265	0.183
Share of female members aged 56 and over	0.060	0.167
Number of observations	46836	

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

Notes: Categories omitted in the characteristics of household heads are being widowed or divorced (marital status) and having not attended school (educational attainment).

Appendix Table1[C]: Summary statistics of village characteristics for rural Indonesia (1997)

Village characteristics	Mean	SD
Characteristics of and heterogeneity in village residents		
Imputed household per capital expenditure (PCE) (1,000 rupiah, 1995 Jakarta prices)	46.536	10.375
Coefficient of variation (CV) of imputed PCE	0.289	0.092
Total per household grant value (1,000 rupiah, 1995 Jakarta prices)	16.941	16.099
Density (100 persons per hectare)	0.036	0.061
Share of educated household heads who have completed the primary degree or above	0.471	0.262
Education Gini index	0.386	0.216
Characteristics of village head		
1{village head is aged 39 or less}	0.332	0.471
1{village head is aged 39 or less and completed high school or higher education}	0.143	0.350
1{village head is aged between 40 and 47}	0.310	0.463
1{village head is aged between 40 and 47 and completed junior high school or higher education}	0.169	0.375
1{village head is aged 48 and above and completed junior high school or higher education}	0.156	0.363
1{village head is female}	0.014	0.119
Characteristics of village administrative and social institutions		
1{village government (LKMD) is established} * 1{village is outside Java}	0.389	0.488
1{village government (LKMD) is established} * 1{village is in Java}	0.241	0.428
1{village has farmers' associations}	0.645	0.478
1{village has groups of advisors such as agricultural extension and health and nutrition}	0.629	0.483
Availability of financial institutions		
1{village has at least one cooperative}	0.205	0.404
1{village has at least one bank}	0.123	0.328
1{village received at least one credit program in the previous year}	0.343	0.475
Transportation and communication infrastructure		
1{village's main access is through land}	0.879	0.327
1{village's main access is through land and the inter-village road is made of asphalt or hardened}	0.382	0.486
1{village has access to public transportation within the village}	0.388	0.487
1{village has a public television}	0.260	0.439
1{village has a post office}	0.068	0.251
Experiences of negative shocks		
1{village experienced natural disasters such as droughts, floods, earthquakes and volcano eruptions at least once in the past three years}	0.381	0.486
1{village had epidemic such as vomiting, diarrhea, and dengue fever in the previous year}	0.228	0.419
Grant receipt status		
1{village's grant status in 1993 depended on field officers' subjective perceptions}	0.361	0.480
1{village was newly added to the treatment group in 1995}	0.142	0.349
1{village was newly added to the treatment group in 1996}	0.252	0.435
1{village dropped out of the treatment group in 1995 or 1996}	0.043	0.203
Difference between the village score and the 1993 provincial threshold	-0.263	1.189
Difference between the village score and the 1994 provincial threshold	0.411	1.421
1{village was funded in 1993 or 1994 despite the rules suggesting no funding}	0.015	0.122
Regional dummies		
Sumatera	0.168	0.374
Java and Bali	0.262	0.440
Nussa Tenggara	0.250	0.433
Kalimantan	0.108	0.311
Sulawesi	0.091	0.288
Number of observations (villages)	2832	

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

Notes: 1. Omitted categories are East (regional dummies) and villages headed by persons aged 48 or above.

2. 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.

Appendix Table 2: Pre-program relationship between household PCE and characteristics (1993 and 1994, rural Indonesia)

Outcome = Household PCE (Rupiah, 1995 prices)	
Characteristics of the household head	
Educational attainment	
Attended but no degree	443.808
	[0.094]*
Primary degree	2,276.61
	[0.000]***
Secondary degree	15,182.19
	[0.000]***
1{Can speak Indonesian}	3,064.76
	[0.000]***
1{Can read and write alphabet}	1,022.47
	[0.000]***
Age	397.461
	[0.000]***
Age^2	-3.266
	[0.000]***
1{Male}	-1,538.00
	[0.000]***
1{Single}	6,687.94
	[0.000]***
1{Married}	3,125.72
	[0.000]***
Characteristics of the housing	
Floor area (1000m^2)	68,433.57
	[0.000]***
1{Wall is made of inferior materials}	-3,087.55
	[0.000]***
1{Roof is made of inferior materials}	-3,719.36
	[0.000]***
1{Floor is made of inferior materials}	-4,552.76
	[0.000]***
1{Inferior source of light is used}	-8,066.47
	[0.000]***
1{No toilet facility}	319.332
	[0.004]***
Demographic characteristics	
1{Household size = 2}	-25,650.35
	[0.000]***
1{Household size = 3}	-35,281.77
	[0.000]***
1{Household size = 4}	-41,608.42
	[0.000]***
1{Household size = 5}	-45,869.71
	[0.000]***
1{Household size = 6}	-49,401.85
	[0.000]***
1{Household size >= 7}	-52,853.19
	[0.000]***
Share of members aged 0-4	-13,536.10
	[0.000]***
Share of members aged 5-15	-9,101.91
	[0.000]***
Share of female members aged 16-55	-6,403.32
	[0.000]***
Share of male members aged 16-55	9,872.63
	[0.000]***
Share of female members aged 56 and over	-16,089.34
	[0.000]***
Observations	250974
R-Squared	0.8
F-stat	19426

Sources: 1993 and 1994 SUSENAS

Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.

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

Appendix Table 3: Household characteristics associated with IDT eligibility, participation, and loan size (1997, Rural Indonesia)

	(1)	(2)	(3)	(4)	(5)
	1{Household is eligible}	1{Household has participate}	1{Household has participated given eligibility}	Loan size given participation	Loan size including zeros
Characteristics of the household head					
Educational attainment					
Attended but no degree	-1.794	-1.605	-2.668	-29.307	0.828
	[1.039]*	[1.028]	[21.244]	[15.183]*	[1.035]
Primary degree	-3.477	-2.785	7.762	-25.585	1.985
	[1.152]***	[1.138]**	[22.372]	[14.140]*	[1.127]*
Secondary degree	-14.206	-12.071	16.619	-65.883	0.973
	[1.260]***	[1.242]***	[23.611]	[15.632]***	[1.310]
1{Can speak Indonesian}	1.453	1.081	-18.997	-6.518	0.284
	[0.848]*	[0.814]	[19.889]	[10.037]	[0.799]
1{Can read and write alphabet}	2.571	2.671	9.654	30.932	-0.374
	[1.025]**	[1.018]***	[18.695]	[13.540]**	[1.061]
Age	0.575	0.613	-0.207	2.463	0.288
	[0.092]***	[0.090]***	[2.716]	[1.065]**	[0.106]***
Age^2	-0.007	-0.007	0.003	-0.028	-0.003
	[0.001]***	[0.001]***	[0.030]	[0.011]**	[0.001]***
1{Male}	7.825	6.818	48.594	50.274	2.58
	[1.115]***	[1.103]***	[23.321]**	[11.702]***	[1.261]**
1{Single}	-2.412	-2.109	-17.564	-22.059	-2.031
	[1.373]*	[1.363]	[35.833]	[17.110]	[1.893]
1{Married}	0.425	0.678	-4.577	2.868	-0.477
	[0.888]	[0.890]	[21.492]	[11.174]	[0.948]
Demographic characteristics					
Number of household members	1.376	1.326	2.511	6.841	0.301
	[0.136]***	[0.132]***	[3.001]	[1.552]***	[0.143]**
Share of members aged 0-4	6.627	6.473	-15.863	23.344	2.878
	[2.514]***	[2.437]***	[80.162]	[28.163]	[2.824]
Share of members aged 5-15	6.384	6.682	22.99	55.56	3.894
	[2.173]***	[2.097]***	[70.970]	[23.462]**	[2.435]
Share of female members aged 16-55	6.623	6.636	58.33	32.694	4.211
	[2.257]***	[2.200]***	[72.468]	[23.723]	[2.711]
Share of male members aged 16-55	1.57	3.178	6.655	35.523	4.991
	[1.909]	[1.825]*	[65.966]	[24.061]	[2.198]**
Share of female members aged 56 and over	-0.527	1.713	48.977	2.809	7.56
	[2.312]	[2.262]	[90.573]	[26.178]	[2.956]**
Characteristics of the housing					
Floor area (1000m^2)	-41.868	-40.503	90.79	-176.542	3.65
	[6.478]***	[6.306]***	[117.060]	[52.370]***	[7.733]
1{Wall is made of inferior materials}	5.213	4.709	-11.89	0.532	0.674
	[0.659]***	[0.648]***	[15.637]	[8.086]	[0.721]
1{Roof is made of inferior materials}	1.577	1.391	7.108	17.12	-0.123
	[0.661]**	[0.655]**	[15.222]	[8.906]*	[0.645]
1{Floor is made of inferior materials}	5.731	5.405	21.704	30.195	1.174
	[0.637]***	[0.629]***	[13.641]	[7.006]***	[0.652]*
1{Inferior source of light is used}	2.602	1.674	-11.841	1.503	-0.764
	[0.697]***	[0.666]**	[16.768]	[8.176]	[0.691]
1{No toilet facility}	2.7	1.727	-37.983	-6.944	-0.962
	[0.633]***	[0.616]***	[13.243]***	[8.925]	[0.684]
Observations	46836	46836	16048	46836	19091
Villages	2832	2832	2241	2832	2382
F-stat	59.45	51.67	1.35	9.45	2.69

Sources: 1997 SUSENAS
Notes: 1. p values in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%.
2. The regression also includes the village-level fixed effects.
3. All the loan values are in terms of 1,000 rupiah, 1995 Jakarta prices.