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CLIENTELISTIC POLITICS AND PRO-POOR TARGETING:

Rules versus Discretionary Budgets*

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Abstract

Past research has provided evidence of clientelistic politics in delivery of program benefits by local governments (gram panchayats (GPs)), and manipulation of GP pro- gram budgets by legislators and elected officials at upper tiers in West Bengal, India. Using household panel survey data spanning 1998-2008, we examine the consequences of clientelism for distributive equity. We find that targeting of anti-poverty programs was progressive both within and across GPs, and is explained by greater 'vote responsive- ness' of poor households to receipt of welfare benefits. Across-GP allocations were more progressive than a rule-based formula recommended by the 3rd State Finance Commis- sion (SFC) based on GP demographic characteristics. Moreover, alternative formulae for across-GP budgets obtained by varying weights on GP characteristics used in the SFC formula would have improved pro-poor targeting only marginally. Hence, there is not much scope for improving pro-poor targeting of private benefits by transitioning to formula-based budgeting.

Keywords: clientelism, governance, targeting, budgeting

JEL Classification: H40, H75, H76, O10, P48.

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1 Introduction

A hallmark of good governance is the extent to which governments succeed in delivering welfare benefits to those most in need. This requires a conjunction of suitable institutions and devolution of decision-making authority to those with both suitable information regarding deservingness of different regions, household units within those regions, and the incentive to prioritize the needy. An important argument in favor of decentralized governance has been the superiority of local information. On the other hand there are concerns about lack of accountability or about perverse incentives of local government officials (World Development Report 2004, Mookherjee (2015)). Accountability concerns arise from evidence of political distortions such as elite capture or political clientelism (Mansuri and Rao (2013), Bardhan and Mookherjee (2012)). These raise questions regarding the suitable design of delivery mechanisms, and the extent to which authority should be delegated to local governments.

We address this question in the context of rural West Bengal, a state in eastern India. We examine whether moving from discretionary allocation of benefits across local government to formula based allocations would improve targeting of anti-poverty programs. Recent re- search has found increasing evidence of political clientelism in the delivery of benefits by West Bengal local governments.1 Using household data covering 2004-2011, Bardhan et al (2020) showed votes of household heads responded to receipt of excludable private benefits disbursed by local governments gram panchayats (GP) at the bottom-most tier, but not to provision of non-excludable local public goods. Mirroring this, middle tiers of government at the district and block level responded to increased political competition by manipulating program budgets of lower tier GPs for private benefits but not for infrastructure programs.2

In particular, GPs controlled by the same party at both tiers received higher budgets, while those controlled by rival parties experienced severe cuts. Dey and Sen (2016) and Shenoy and Zimmerman (2020) provide evidence of a similar phenomenon during the post-2011 period featuring a different ruling party in most areas: winners of close election races raised em- ployment program scales only in aligned GPs, presumably rewarding GP areas and leaders who helped deliver votes for their party.

Hence, there is clear evidence that discretionary control over benefit distribution is exer- cised opportunistically in West Bengal, both within and across GPs. We examine the resulting consequences for pro-poor targeting of welfare benefits where the poorest households are the intended beneficiaries. Using a panel household survey spanning 1998-2008, we evaluate the distribution of benefits in relation to proxy measures of the deservingness of households. We then estimate possible impacts on pro-poor targeting from switching to a formula-bound programmatic system of transfers which would remove scope for discretion of local officials.

Conceptually, the extent of likely improvement from a centralized formula would depend on informational advantage of local officials relative to information contained in budgeting formulae, as well as targeting incentives of the former. At one extreme, a centralized formula-based program could achieve perfect targeting if the state had perfect information about the distribution of socio-economic status (SES) across individual households, and could cost-lessly deliver benefits directly to them. In practice, upper level governments (ULGs) at the national or state level in India neither have such information, nor do they have the capacity to transfer benefits directly to households. The level of disaggregation of governments information regarding economic backwardness is low being limited to village census records, supplemented by household sample surveys which are representative at best at the district level. Moreover, a large fraction of the rural poor do not have functioning bank accounts. Even the biometric citizen identification Aadhar cards that have been rolled out nationwide over the past decade are yet to achieve universal coverage, cannot be integrated with bank accounts, and contain many errors.3

Hence, GPs have traditionally been delegated the task of identifying SES status of households within their jurisdiction, selecting beneficiaries and delivering various benefit (mostly in-kind) programs. Middle level governments (MLGs hereafter) at block and district lev- els have been delegated responsibility of allocating program budgets across GPs within their jurisdiction, based on their knowledge of the distribution of poverty and need across GP areas. Owing to weaknesses in informational and delivery capacity of ULGs, a formula-bound program would perforce have to devolve within-GP allocation powers to GPs. Hence, the scope of programmatic policy reforms would be restricted to determining GP program budgets, thereby affecting resource allocations across rather than within GPs. A recent World Bank program for strengthening local governance in West Bengal involving 1000 GPs has been based on direct grants to GPs based on transparent formulae, constitutes an example of such an approach.4

Imperfections in information available to the state government about distribution of poverty across villages on which formula bound GP budgets would be based, would inevitably cause targeting errors. There would be errors both of inclusion (prosperous villages with few poor households that are misclassified as poor villages would end up receiving large budgets) and of exclusion (poor villages misclassified as prosperous failing to qualify for program grants). It is a priori unclear whether the formula bound program would generate better pro-poor targeting compared to the existing discretionary system. The net result would depend on (a) the superiority of ‘local soft’ information available to MLGs relative to the ‘hard’ information available to ULGs regarding the distribution of poverty across GP areas, and (b) incentives generated by political clientelism for MLGs to target benefits towards truly poor areas.

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[1]See Bardhan et al (2010, 2015, 2020), Bardhan and Mookherjee (2012), Dey and Sen (2016), Shenoy and Zimmerman (2020).

[2]The causal effect of changing political competition was identified by comparing changes in budgets of GPs redistricted in 2007 to more contested state assembly constituencies, with others not redistricted or those redistricted to less contested constituencies

[3]For a recent discussion of these problems, see Dreze, Khera and Somanchi (2020).

[4]See https://projects.worldbank.org/en/projects-operations/project-detail/P159427

As previous literature indicates, the latter in turn is likely to depend on whether elections in poorer regions are less contested, or feature different patterns of political alignment between MLGs and ULGs. For instance, improvements in pro-poor targeting would result from a transition to formula-based budgets if elections in poorer areas were less contested, or resulted in lack of vertical alignment of political control. Also relevant is the relative responsiveness of votes of the poor and non-poor to benefit delivery. Some have argued that clientelism creates a bias in favor of distributing benefits towards the poor, since their votes are cheaper to 'buy'. Others have argued that the poor vote is determined more by 'iden- tity' considerations and less by actual governance performance, while non-poor and better educated voters are more prone to swing based on benefits received. It is therefore hard to predict a priori whether political opportunism for MLGs in a clientelistic setting would translate into a pro- or anti-poor bias.

Hence, the effect of moving to formula based GP budgets is an empirical question, which we address in this paper. It is based on actual targeting patterns estimated on the basis of household panel surveys in a sample of 59 GPs covering 2400 households over a ten year period 1998-2008. Besides declarations by household heads of benefits received, the surveys include household demographic, asset and income information which allow us to classify them into categories of ultra-poor, moderately poor, and marginally poor. Our definition of these categories is based on whether three, two, or one of the following criteria are satisfied by any given household: if it is landless (owns no agricultural land), if the head is uneducated (zero years of schooling), and if the household belongs to a scheduled caste or tribe (SC/ST). Apart from capturing the multidimensionality of poverty, this method accurately measures the depth of poverty: the distribution of annual reported income, the value of land owned, or of the reported value of the dwelling of successive classes are ordered by first order stochastic dominance. It has the virtue of not being influenced by transitory shocks, and is more easily and precisely measured compared to income or consumption based measures of poverty. Moreover, income or consumption are unlikely to be observable by local government officials, unlike the proxies we use. Hence, patterns of targeting based on these proxies seem more appropriate means of describing and evaluating the targeting decisions that they actually made.

For outcomes of targeting, we examine three different measures for any given household in a given year: (i) the number of employment benefits received (i.e. number of household members employed in GP employment programs), (ii) total number of all other anti-poverty benefits (aggregating subsidized loans, low income housing, toilets, drinking water access, old age or widow benefits, and below-poverty-line (BPL) cards that provide access to many other benefits) received, and (iii) agricultural mini-kits (containing seeds, pesticides and fer- tilizers at highly subsidized rates). The first two constitute anti-poverty and income security programs, while the third is an agricultural development program. It is difficult to estimate the monetary values of these various benefits in the absence of reliable data on local prices and wages, and the problems with recall errors or other biases that would inevitably arise if we were to rely on household reports. We use Poisson count regressions since households can receive more than one benefit per year. Out of the households that reported receiving em- ployment benefits, 5% report receiving two benefits per year. The corresponding number for non-employment anti-poverty benefits is 3% and for minikits it is zero. The outcome measure for category (ii) is likely to be subject to biases owing to aggregation across diverse benefits.

Nevertheless, we shall see that results do not vary significantly between this category of benefits and the employment programs, suggesting that our results are robust with respect to this concern.

The within-GP targeting pattern for anti-poverty programs (which conditions on the bud- get the GP receives from MLGs) reveals a clear bias in favor of poor households. Poorer households were more likely to receive either an employment benefit, or any of the other anti-poverty benefits. On the other hand, the allocation of subsidized farm inputs was biased in favor of the non-poor who owned more agricultural land. Hence, the direction of targeting of within-GP allocations appear to be in the 'right' direction, varying with the extent to which the corresponding benefit would be likely to benefit the recipient.

For all programs, increased GP program budgets (proxied by per household benefits distributed in the GP) resulted in near-uniform increases in allocations to all households irrespective of poverty status. The targeting patterns are robust to varying specifications, either of functional form (linear versus Poisson), controls for village characteristics or inclusion of year, GP or district fixed effects. The results for the linear specification are also unchanged in an instrumental variable (IV) regression where we instrument for the per household GP benefit by the corresponding per household GP benefit in all others GPs in the same district in that year (a la Levitt-Snyder (1997)), while controlling for district fixed effects. The fact that conditional on GP budgets the targeting patterns are unaffected by replacing GP fixed effects by district fixed effects is consistent with the hypothesis that GP budgets represent the primary channel by which targeting is affected by actions of MLGs. And the robustness of targeting patterns with respect to the potential endogeneity of GP budgets indicates that the estimated impact of GP budgets can be interpreted causally. One can therefore use them to predict the targeting impacts of changing the way GP budgets are set.

Next we examine how observed GP budgets varied across GPs. These were also progressive: GPs with a higher household proportion of ultra or moderately poor households were allocated higher budgets. This indicates that political incentives of elected officials were aligned in favor of delivering welfare benefits to the poor. To explain this result, we rely on the model of clientelistic allocation in Bardhan et al (2020). Within GPs, officials of both incumbent and challenger party are motivated to deliver benefits to those who are most likely to respond with their votes in the subsequent election. Using data on political support expressed by household heads, and extending the method used in Bardhan et al (2020), we provide evidence showing that the political support of poorer households was more responsive to benefits than non-poor households. This is consistent with the common wisdom regarding clientelism (Stokes (2005), Stokes et al (2013)), as well as with the observed intra-GP targeting patterns. Regarding across-GP allocation decisions of MLGs, the model predicts that the progressivity of these allocations depend on how electoral competition and vertical alignment (of political control between GPs and upper tiers) vary across regions with different poverty rates. We find the absence of any significant correlation between either competitiveness and alignment with the poverty rates across GP areas. Hence we infer that the progressivity of cross-GP budget allocations was driven primarily by the higher vote responsiveness of poor households.

The cross-GP allocations actually observed turn out to have been more progressive than the formula for allocation of fiscal grants to GPs recommended by the 3rd State Finance Commission (SFC) of West Bengal. The SFC formula incorporates six village characteristics from the Census and some household surveys: population size, SC/ST proportion, proportion of female illiterates, a food insecurity index, proportion of agricultural workers, village infrastructure, and population density. Across GPs, SFC-recommended grants turned out to be less positively correlated (compared with actual allocations) with the village proportion of (at least moderately) poor households.

This suggests that transitioning to GP budgets based on the SFC formula would have resulted in less pro-poor targeting. To verify this, we use the estimated within-GP targeting pattern to predict how the expected number of benefits would have changed for any given household in the sample. We aggregate this to estimate the state-wide share of benefits accruing to different poverty groups. The exact results depend on some details regarding the specific method of budget reallocation and the estimation procedure. Budgets could be reallocated across GPs within each district, or across all GPs in the state. Budget balance within the GP could be achieved by scaling predicted changes in within-GP allocations proportionally (proportional scaling). Alternatively, the allocations for poor groups could be predicted on the basis of the estimated within-GP targeting patterns, with the non-poor picking up the slack being treated as residual claimants (residual scaling). The results turn out to be qual- itatively similar across these different approaches. With proportional scaling, the resulting impacts on targeting are negligible, while in the case of proportional scaling poor groups end up with fewer expected welfare benefits under an SFC-formula based system.

Finally, we examine whether variations on the weights used in the SFC formula could have improved targeting beyond the observed allocations. For employment benefits and proportional scaling, we estimate that the share of the ultra-poor could at best have been increased from 18.4 to 19.2%, and the moderately poor from 35.9% to 36.3%. The changes in shares of non-employment anti-poverty benefits are of a similar order of magnitude.

In summary, the scope for improving pro-poor targeting by switching to formula based GP budgets is limited at best, as long as the formula is based on indicators used by the West Bengal SFC. This owes partly to a degree of pro-poor accountability in West Bengal local government, and partly to superior information of local officials about the distribution of need compared with measures utilized by the SFC. For formula-based budgeting to achieve further improvements, they would have to rely on better information regarding ownership of key assets of land and education at the household level.

Related to this point, it is important to note that we are not addressing the broader ques- tion of the overall anti-poverty effects of clientelism. Our analysis concerns only effects of discretionary budgeting on pro-poor targeting of private benefits within a clientelistic regime. By focusing on pro-poor targeting or vertical equity, we are ignoring horizontal equity considerations, e.g., the allocation of benefits between different poor groups, either between or within villages. Indeed, by showing how this allocation seems to have been manipulated for political purposes, the existing literature has already demonstrated patterns of unfairness. Another important dimension we have ignored in this paper is insurance with respect to uncertain shocks to household or village needs. Moreover, as often alleged, clientelism could cause under-supply of local public goods essential for long-term reduction of poverty, and undermine political competition, transparency, state legitimacy and rule of law.

Our work relates to some recent literature studying the implications of moving from discretionary to formula based program grants in Brazil (Azulai (2017), Finan and Mazzocco (2020)), and in drought relief declarations in south Indian states (Tarquinio (2020)). The results of these papers indicate more significant targeting benefits than we find in West Bengal, thus suggesting that the expected results of transitioning to formula based budgets are context-specific. On the other hand, our main result concerning pro-poor targeting of political clientelism echoes broader arguments made by Holland (2017) concerning redistributive benefits of 'forbearance' or lack of enforcement of property laws by governments against specific citizens for political reasons in many Latin American countries. In similar vein, Alatas et al (2012) show that benefits of targeting that could be achieved by formulae based on household based proxies of poverty in Indonesia would only be marginally superior to those achieved by local community groups. Their focus, however, is on within-village targeting, whereas our paper deals with the implications of alternative ways of deciding across-village allocations.

Section 2 provides details of the setting and describes the data. Section 3 then presents evidence on within-GP targeting patterns, and Section 4 on across-GP targeting and how it would be impacted by switching to formula based GP budgets. Finally Section 5 concludes with some qualifications and directions for future research.

2 Context, Data and Descriptive Statistics

Each Indian state has a hierarchy of local governments (panchayats) in rural areas that deliver diverse in-kind benefits to households living in villages. Most of these programs are financed by central and state governments. District-level governments, called zilla parishads (ZPs), allocate funds to middle-tier governments at the 'block' level, which comprise an elected body panchayat samiti (PS) and appointed bureaucrats in the Block Development Offices. The middle tier then allocates funds to bottom-tier gram panchayats (GPs) within their block, who in turn distribute benefits across and within villages in their jurisdiction. Each GP over- sees 10-15 villages, and each village in turn includes an average of 300 households. GPs also administer rural infrastructure projects, in which they employ the local population. Despite being subject to oversight both below (from village assembly meetings) and above (middle level governments that approve projects, expenditures and audit accounts), GPs exercise con- siderable discretion in their allocation and project decisions. MLG officials face considerably less scrutiny, as there are no stated criteria for horizontal allocation of funds or project ap- provals across GPs reporting to them. The near-complete absence of any transparency in across-GP allocations allows MLG officials with substantial discretionary authority.

Our data on program benefits received by households comes from two rounds of longitudinal household surveys carried out in 2004 and 2011. The survey includes 89 villages in 57

GPs spread through all 18 agricultural districts of West Bengal, and has been used in previous papers (Bardhan et al (2020)). There are over 2400 households in the sample, amounting to approximately 25 households per village. Households within a village were selected by sampling randomly in different land strata. Table 1 provides a summary of the demographic characteristics of these households. Over half own no agricultural land, nearly one in three are SC/ST, and one-third household heads are uneducated. Agricultural cultivation is the primary occupation among the landed, while the landless are primarily workers relying on labor earnings.

Table 1: Summary Statistics: Demographics

Agri Land Owned (acres)	No. of Households	Characteristics of Head of Households				
		Avg. Age	% Males	Years of Schooling	% SC/ST	% in Agriculture
Landless	1214	45	88	6.6	37.4	26
0-1.5	658	48	88	7.8	38.9	65
1.5-2.5	95	56	92	10.8	22.4	82
2.5-5	258	58	93	11.1	27.1	72
5-10	148	60	89	12.5	26.1	66
> 10	29	59	100	13.9	30.9	72
All	2402	49	89	8.0	35.4	47

Note. This table provides demographic characteristics of the head of households (who were the main respondents to the survey) in 2004. % Agriculture refers to percentage of household heads whose primary occupation is agriculture.

The period of our study is 1998-2008, spanning two consecutive elected local govern- ments. Since our focus is on political clientelism, we focus attention on excludable private benefit programs distributed through the GP. The most important of these is employment in lo- cal infrastructure construction programs managed by the GP, such as Jawahar Rozgar Yojana (JRY), National Rural Employment Guarantee Act (NREGA) and Member of Parliament Local Area Development Scheme (MPLADS). Mostly carried out in the lean agricultural season between March and July, they provide employed households the opportunity to earn a wage set statutorily above the average market wage rate. In years of low rainfall when private employment opportunities and wages are low, they are an important source of income protection for poor households. Other anti-poverty programs earmarked exclusively for low SES households include subsidized loans, housing/toilet construction subsidies, Below Poverty Line (BPL) cards entitling holders to subsidized food grains and other household items. GPs also help distribute agricultural minikits that contain subsidized seeds, fertilizers, and pesticides, but this is an agricultural development program rather than an antipoverty program. We will see that the targeting patterns for these farm subsidies differ substantially from all the other programs. Table 2 shows the percentage of households receiving at least one benefit in the two panchayat terms.

Table 2: Percentage of Households Receiving At Least One Benefit

	1998-2003	2004-2008
Employment	6.77	24.22
Non-employment Anti-Poverty	35.12	22.33
Farm Subsidy	0.97	7.21

Our data includes different dimensions of low socio-economic status (SES): whether a household belongs to an SC or ST, whether it is landless, and whether head of household is uneducated. We classify households into four groups: ultra-poor, moderately poor, marginally poor, and non-poor depending on whether all, two, one or none of these conditions apply. This is a measure of the number of dimensions on which a household is poor. It also cor- responds to more standard measures used to measure the depth of poverty. Table 3 shows regressions of annual reported income, acres of agricultural land owned, and the value of the principal dwelling of the household on dummies for these different poverty classes, after controlling for village fixed effects. Compared with the non-poor, households in any of the poverty groups earn significantly lower incomes, own less land and less valuable homes on average.

Table 3: Income/Wealth Variations Across Poverty Groups

	Reported Income (Rupees Lakhs) (1)	Agricultural Land (Acres) (2)	Value of House (Rupees Lakhs) (3)
Ultra Poor	-0.477***	-2.897***	-1.263***
	(0.080)	(0.246)	(0.152)
Moderately Poor	-0.397***	-2.519***	-0.989***
	(0.052)	(0.201)	(0.129)
Marginally Poor	-0.263***	-1.775***	-0.565***
	(0.051)	(0.197)	(0.111)
Observations	2256	2256	1691
Adjusted R^2	0.097	0.302	0.238
Mean Dependent Variable	0.371	1.241	0.848
SD Dependent Variable	0.759	2.388	1.214
Village Fixed Effects	YES	YES	YES

Note: This table examines the relationship between our poverty measures and reported income/wealth in the 2004 household survey. The precise reported measure used is indicated at the top of each column. All specifications include village fixed effects. Robust standard errors are in parentheses, clustered at GP level.

Figure 1 depicts the distribution of income and wealth by poverty groups. For each of the measures of socio-economic status, the distributions across poverty groups are ordered by first order stochastic dominance. This supports our interpretation of the poverty groups - ultra and moderately poor households have a higher depth of poverty compared to marginally poor groups. Hence, we will use these as definitions of poverty for the remainder of the paper.

Figure 1: Distribution of Income and Wealth by Poverty Groups

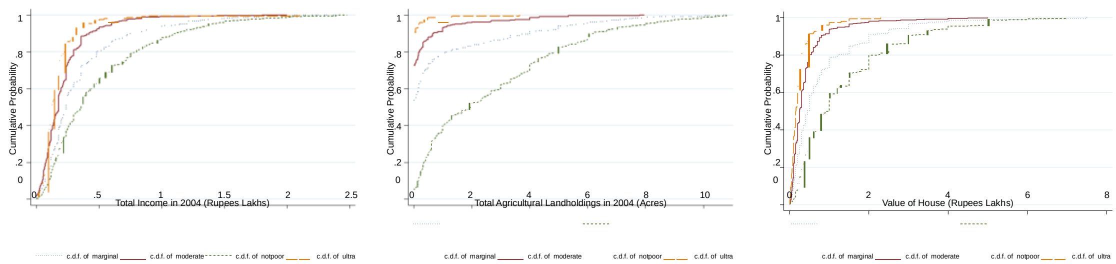


Table 4: Poverty Groups: Demographic Share and Reported Benefits

Group g	Demographic Share	Share of Reported Benefits			Percentage of Households Receiving Benefits		
		Employment	Anti-poverty	Farm Subsidy	Employment	Anti-poverty	Farm Subsidy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ultra Poor	8.53	18.38	12.37	1.59	50.00	62.89	1.55
Moderately Poor	27.56	35.91	31.51	12.70	35.41	50.40	3.51
Marginally Poor	38.33	30.64	33.71	42.33	23.74	43.81	8.83
Non-poor	25.58	15.07	22.41	43.39	18.38	45.53	13.92

Note: For each type of benefit k, 'Share of Reported benefits' $= \frac{\text{Total benefits of type } k \text{ between 1998-2008 received by households in group } g}{\text{Total benefits of type } k \text{ disbursed between 1998-2008}}$ and

'Percentage of Households Receiving Benefits' $= \frac{\text{Total number of households in group } g \text{ that received at least one benefit of type } k \text{ between 1998-2008}}{\text{Total number of households in group } g}$

Table 4 provides the demographic shares and the share of benefits for each group. In our sample, the proportions of households that were ultra-poor, moderately poor and marginally poor was 8.5%, 27.6% and 38.3% respectively. The share of employment and non-employment anti-poverty benefits for ultra and moderately poor households were higher than their demo- graphic shares. However, the opposite is the case for farm subsidies. Columns (5)-(7) show for each group the proportion of households receiving a benefit of a given type. A signifi- cantly higher proportion of ultra poor households receive employment and non-employment anti-poverty benefits compared to other groups. The opposite is true for farm subsidies.

3 Within-GP Targeting

In this section we examine targeting patterns within GPs. We start with the following Poisson count regression specification for each type of benefit k:

$$b_{ikpgt} = \exp(\beta_k * B_{kgt} + \sum_p \delta_{pk} d_{ip} + \sum_l \gamma_{kl} * X_{v(i)l} + \eta_{kg} + \alpha_{kt})$$

where

- bikpgt: number of benefits of type k received by household i belonging to group p in GP g in year t

- Bkgt: GP g budget estimate (per HH number of benefits of type k in g sample) in year t

- dip: dummy for poverty group p of i

- Xv(i)l: i’s village v(i) characteristic l (population, distribution)

- ηkg and αkt: GP/district and year dummies resp.

Table 5 presents the results for each type of program, along with a corresponding linear (OLS) specification. The coefficients of the Poisson regression (expected increase in log benefits associated with a unit increase in the regressor) have a different interpretation from that in the OLS regression (expected increase in benefits associated with a unit change in regressor), and are thus not directly comparable. The regressors include the household’s poverty status (with the non-poor serving as the default group), the GP budget (proxied by the number of benefits per household in the GP sample for that year), and a number of characteristics of the village in which the household resides: size (number of households in the village), and the proportion of households in each poverty group in the village. ‘Villages’ are defined by the Census; they correspond to sub-units within the GP jurisdiction. Each GP jurisdic- tion includes between 8-15 villages. Controls include either district or GP fixed effects, and year dummies. Standard errors are clustered at the GP level. We show results for three pro- grams respectively: employment programs, benefits aggregated across all other anti-poverty programs, and subsidized farm inputs.

Note first that the estimated coefficients of household poverty status change little across the GP and district fixed effect versions of the Poisson regression (first two columns for each program). Moreover the Poisson and OLS linear regression versions with district fixed effects (second and third columns in each set) yield qualitatively similar results. Time-varying across-GP targeting differences are driven by corresponding temporal variations in their respective program budgets, whereas the other non-time-varying regressors capture within-GP targeting patterns. In the specification used in this table, the underlying assumption is that the within and across-GP targeting patterns are orthogonal; we relax this assumption later. Table 5 shows that the within-GP targeting of anti-poverty program benefits is progressive: poorer households receive more benefits. The pattern is exactly the opposite for subsidized farm inputs. Hence, GPs tends to distribute farm inputs quite differently — reflecting either normative consideration of delivering benefits to those that would value them the most, or landed elite appeasement/capture that may co-exist with clientelism (as argued in Bardhan and Mookherjee (2012)).

Table 5: Within-GP Targeting Poisson Regression: GP vs District Fixed Effects

	Dependent Variable: Number of Benefits Received								
	Employment Benefit			Non-employment Anti-poverty Programs Poisson			Subsidized Farm Inputs		
	Poisson (1)	Poisson (2)	OLS (3)	Poisson (4)	(5)	OLS (6)	Poisson (7)	Poisson (8)	OLS (9)
GP Benefits k	0.162***	0.142***	0.011***	0.124***	0.109***	0.010***	0.137**	0.112***	0.009***
	(0.028)	(0.019)	(0.002)	(0.021)	(0.014)	(0.002)	(0.055)	(0.034)	(0.002)
Ultra Poor	1.484***	1.492***	0.057***	0.655***	0.658***	0.046***	-2.119***	-2.141***	-0.011***
	(0.197)	(0.199)	(0.009)	(0.121)	(0.121)	(0.010)	(0.718)	(0.717)	(0.004)
Moderately Poor	1.053***	1.071***	0.033***	0.532***	0.536***	0.034***	-1.245***	-1.258***	-0.009**
	(0.170)	(0.174)	(0.007)	(0.096)	(0.096)	(0.007)	(0.417)	(0.417)	(0.004)
Marginally Poor	0.520***	0.531***	0.014***	0.219***	0.221***	0.014***	-0.406**	-0.413**	-0.004*
	(0.142)	(0.144)	(0.004)	(0.071)	(0.071)	(0.004)	(0.177)	(0.176)	(0.003)
Number HH in Village	0.002***	-0.000	-0.000	0.000	-0.000	-0.000	-0.003***	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Proportion of Ultra Poor	-1.210	-2.110**	-0.087***	0.534	-1.150	-0.086	2.522	-3.215	-0.022
	(1.307)	(0.972)	(0.033)	(1.117)	(1.223)	(0.060)	(1.970)	(2.328)	(0.013)
Proportion of Moderately Poor	-0.444	-0.745	-0.022	-0.139	-0.613	-0.044	1.422	1.042	0.006
	(0.754)	(0.540)	(0.018)	(0.739)	(0.644)	(0.036)	(1.117)	(1.121)	(0.009)
Proportion of Marginally Poor	-0.963*	-0.568	-0.023	-0.032	-0.436	-0.022	-0.995	-1.268	-0.002
	(0.502)	(0.453)	(0.016)	(0.410)	(0.429)	(0.025)	(1.270)	(1.033)	(0.007)
Observations	25025	25025	25025	25025	25025	25025	25025	25025	25025
Mean Dependent Variable	0.033	0.033	0.033	0.064	0.064	0.064	0.008	0.008	0.008
SD Dependent Variable	0.194	0.194	0.194	0.262	0.262	0.262	0.087	0.087	0.087
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
GP FE	YES	NO	NO	YES	NO	NO	YES	NO	NO
District FE	NO	YES	YES	NO	YES	YES	NO	YES	YES

Note.- Observations are at the household-year level, 1998-2008. Dependent variable in columns (1)-(3) is the number of employment benefits received by the household in year t. For columns (4)-(6), the dependent variable is the number of non-employment anti-poverty benefits and for columns (7)-(9), it is the number of subsidized farm inputs. For each type of benefit, the first two columns report the results from a poisson regression while the third column reports estimates from an OLS regression. Regression coefficients in Poisson regressions can be interpreted as the change in log of expected number of benefits associated with a unit change in each regressor. Each specification includes year fixed effects. Whether the specification includes GP fixed effects or district fixed effects is indicated at the bottom of the table. Robust standard errors are in parentheses, clustered at GP level.

A higher proportion of poor households residing in the village generally tends to lower benefits received by a representative household, though these estimates tend to lack statistical significance. These negative effects are more pronounced in the version with district rather than GP fixed effects. Since the regression conditions on the GP program budget, it is likely to arise mechanically from the GP budget constraint, combined with the progressive pattern of targeting within the GP. Since poorer households are more likely to receive benefits than the non-poor, a GP with a larger fraction of poor households and with a given budget will have less available to distribute to non-poor households. It should not necessarily be interpreted as a form of regressivity in the across-GP targeting pattern, which will be manifested in the allocation of budgets across GPs (which will be examined in the next Section).

In order to simulate the within-GP effects of changes in GP budgets, it is important to obtain an unbiased estimate of the causal impact of changing these budgets. The preceding regression estimate of the GP budget effect is subject to various possible biases. First, the GP budget is not directly observed and is measured with error by its proxy, the per household benefit in the sample. The resulting measurement error could result in a downward (attenu- ation) bias. Second, the per capita benefit measure in the GP includes each household in the sample, thereby mechanically inducing a positive bias. Third, GP budget allocations may not be exogenous as they could be driven by political considerations of officials in upper level governments. These unobserved political considerations (competitive stakes, political align- ment, responsiveness of votes to program benefits) could possibly vary across GPs and may be systematically correlated with the regressors, thereby biasing the coefficient estimates in Table 5.

To deal with these concerns, Table 6 presents an instrumental variable (IV) regression for the linear specification, where we instrument for the GP budget by average per household program scale in all other GPs in the district. This is similar to the instrument used in earlier work of Levitt and Snyder (1997) and Bardhan et al (2020). This reflects factors less likely to be correlated with GP-specific unobserved political attributes, such as the scale of the program budget at the district level (determined by financing constraints at the district level), and political attributes of other GPs in the district with which the given GP is competing for funds. As explained in some detail in Levitt and Snyder (1997) and Bardhan et al (2020), under plausible assumptions the resulting IV estimate is likely to be less biased, with the bias tending to vanish as the number of GPs per district becomes large.5

Table 6~~: Within-GP Targeting Regressions with District Fixed Effects – IV Version~~

	Dependent Variable: Number of Benefits Received					
	Employment Benefit		Non-employment Anti-poverty Programs		Subsidized Farm Inputs	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
GP Benefits k	0.01***	0.01***	0.01***	0.02***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Ultra Poor	0.06***	0.06***	0.05***	0.05***	-0.01***	-0.01***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Moderately Poor	0.03***	0.03***	0.03***	0.03***	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Marginally Poor	0.01***	0.01***	0.01***	0.01***	-0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number HH in Village	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Proportion of Ultra Poor	-0.09***	-0.11***	-0.09	-0.20	-0.02	-0.03*
	(0.03)	(0.04)	(0.06)	(0.13)	(0.01)	(0.01)
Proportion of Moderately Poor	-0.02	-0.03	-0.04	-0.07	0.01	0.00
	(0.02)	(0.02)	(0.04)	(0.05)	(0.01)	(0.01)
Proportion of Marginally Poor	-0.02	-0.03	-0.02	-0.03	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)
Observations	25025	25025	25025	25025	25025	25025
Adjusted R^2	0.085	0.079	0.054	0.037	0.092	0.085
Mean Dependent Variable	0.03	0.03	0.06	0.06	0.01	0.01
SD Dependent Variable	0.19	0.19	0.26	0.26	0.09	0.09
Year FE	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES

Note.- Observations are at the household-year level, 1998-2008. Dependent variable in columns (1)-(2) is number of employment benefits received by the household in year t. For columns (3)-(4), the dependent variable is non-employment anti-poverty benefits and for columns (5)-(6), it is number of subsidized farm inputs. For each type of benefit, the first column reports the results from an OLS regression while the second column reports estimates from an IV regression. Each specification includes year and district fixed effects. Robust standard errors are in parentheses, clustered at GP level.

The IV regression includes both year and district fixed effects. For each program, the first column is the OLS regression (reproduced from the corresponding third column in Table 5),

5See Bardhan et al (2020) for details of the first stage regressions and the strength of the instrument in predicting variation in GP budgets.

and the second column is the corresponding IV regression. It is evident that the OLS and IV estimates are very close to one another. Hence, the bias in the OLS regression does not appear to be significant. In what follows, we shall assume that there is no endogeneity bias in the estimated marginal impact of increasing the GP budget.

To predict the number of benefits received by households when GP budgets are reallo- cated according to the formula, our preferred model is the Poisson regression model. This method is appropriate because the log transformation in the Poisson model guarantees that the predicted number of benefits are non-negative. We enrich the specification in Table 5 to allow for interactions between GP budget and household poverty status. Table 7 shows that these interaction coefficients are negative, implying that while poor households continue to receive priority, this priority diminishes as the GP budget expands — increases in the budget are directed more towards non-poor households. These coefficients, however, are quantitatively negligible compared to the corresponding coefficients of the poverty status dummies themselves. Even though there is relatively little heterogeneity in the impact of varying GP budgets across different poverty groups, we will use this extended version of the model in order to improve the accuracy of the predictions.

Table 7: Within-GP Targeting: Poisson Prediction Model

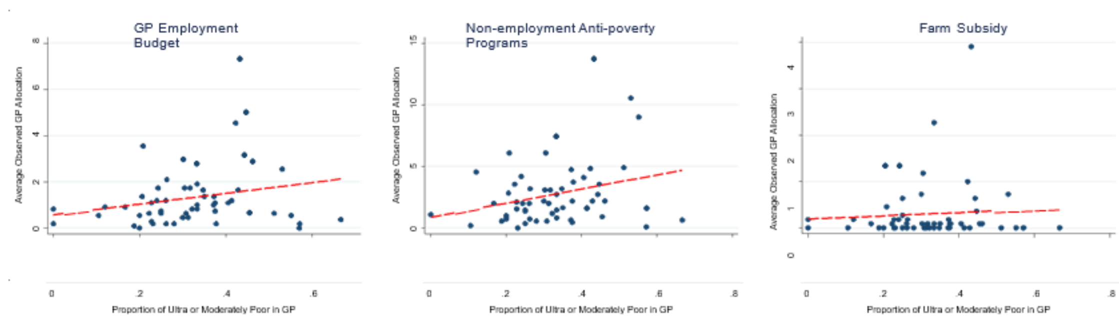
	Dependent Variable: Number of Benefits Received		
	Employment Benefit	Non-employment Anti-poverty Programs	Subsidized Farm Inputs
	(2)	(3)	(4)
GP Budget (per HH benefit)	0.183***	0.147***	0.154***
	(0.027)	(0.022)	(0.059)
Ultra Poor	1.867***	0.870***	-1.164*
	(0.203)	(0.116)	(0.608)
Moderately Poor	1.258***	0.742***	-0.755*
	(0.198)	(0.081)	(0.431)
Marginally Poor	0.554***	0.411***	-0.225
	(0.165)	(0.073)	(0.200)
GP Benefits * Ultra Poor	-0.045***	-0.029***	-0.255***
	(0.009)	(0.009)	(0.083)
GP Benefits * Moderately Poor	-0.025***	-0.028***	-0.053**
	(0.007)	(0.009)	(0.024)
GP Benefits * Marginally Poor	-0.009	-0.027***	-0.017*
	(0.010)	(0.006)	(0.009)
Number HH in Village	0.002***	0.000	-0.003***
	(0.000)	(0.000)	(0.001)
Proportion of Ultra Poor	-1.375	0.465	2.859
	(1.333)	(1.111)	(1.936)
Proportion of Moderately Poor	-0.449	-0.205	1.190
	(0.741)	(0.736)	(1.116)
Proportion of Marginally Poor	-0.903*	-0.109	-1.152
	(0.492)	(0.410)	(1.245)
Observations	25025	25025	25025
Mean Dependent Variable	0.033	0.064	0.008
SD Dependent Variable	0.194	0.262	0.087
Year Fixed Effects	YES	YES	YES
District Fixed Effects	YES	YES	YES

Note.- Observations are at the household-year level, 1998-2008. Dependent variable in column (1) is the number of employment benefits received by the household in year t, column (2) is the number of non-employment anti-poverty benefits, and column (3) is the number of subsidized farm inputs. Each specification is estimated using a Poisson regression model and the coefficients can be interpreted as the change in log of expected number of benefits associated with a unit change in each regressor. Each specification includes year and GP fixed effects. Robust standard errors are in parentheses, clustered at GP level

4 Across-GP Targeting

In this section we examine the targeting patterns in across-GP observed allocations. Figure 2 plots estimated GP budgets against the proportion of households in the village that are ultra or moderately poor, with the red dashed line showing the corresponding OLS linear regression. These regressions all show a positive slope, indicating that the across-GP allocation was progressive.

Figure 2: Across-GP Budget Variations with GP Poverty



4.1 Explaining the Progressivity of Targeting Patterns

To shed light on the role of clientelism in driving the progressive allocation of program benefits, we refer back to the theoretical model of two party electoral competition in a two (middle and lower) tier government hierarchy in Bardhan et. al (2020). Elections are held at both tiers, based on a first-past-the-post contest. The middle tier allocates given program budgets across different GPs at the lower tier, while elected GP officials allocate their assigned budgets across households within the GP. Officials at both tiers use their discretionary allocation powers to maximize the likelihood of re-election of their respective party. Voters assign credit for benefits received to the party controlling the GP, a plausible consequence of the lack of transparency of the budgeting process. With a standard model of probabilistic voting, GP officials of either party allocate their assigned budgets to households most likely to respond with their votes to benefits they receive. Hence within-GP targeting is biased in favor of households with stronger 'vote responsiveness' or 'swing propensity'. Within-GP targeting would therefore tend to be pro-poor if poorer households were more responsive.

We construct political support data from ballots cast by heads of household in the 2011 survey. The process simulated the official "secret ballot" voting process. The households

were provided sample ballots marked with symbols of principal political parties participating in local elections, in which names of the respondents did not appear (and instead replaced by a number assigned by a security code available only to the PIs). The respondents were given the ballot and a locked box. They were allowed to go into a separate room, cast their vote by putting their ballots in the locked box and then return the box to the interviewer. The survey was conducted shortly after the state assembly elections in 2011.

Table 8 reports the results for voting responsiveness to receipt of private benefits (aggregating all three categories of private programs) for the three preceding years 2009-2011 for poor (combining ultra and moderately poor groups) and marginally or non-poor households respectively. The OLS results in column (1) shows that a one standard deviation increase in private benefits received by poor households resulted in a 3.6% higher likelihood for the head of the household to vote for the GP incumbent. Consistent with results in Bardhan et. al (2020), there is no voting responsiveness for public good benefits received, as predicted by the clientelist theory (since public good benefits being non-exclusionary cannot be used as a clientelist instrument to generate votes). Column 3 shows the corresponding OLS estimates for marginally poor and non-poor households. While the coefficient of public benefits fails to be positive and significant, the coefficient of private benefits is one-third the magnitude of the corresponding coefficient for poor households and fails to be statistically significant.

The second and fourth columns show the corresponding IV estimates when benefit distribution within the GP is instrumented by per household supply in the district excluding the GP in question, again in line with the IV strategy in Levitt-Snyder (1997) and Bardhan et al (2020). The IV estimates are substantially larger in magnitude than the OLS estimates, but the qualitative pattern remains the same: only private benefits matter for votes, and they matter much more for poor households. Hence, the result of greater vote responsiveness of the poor is robust to endogeneity concerns for the supply of benefits and help explain why within-GP targeting tends to be pro-poor.

We now turn to the cross-GP targeting pattern, resulting from GP budgetary allocations made by officials at the upper tier. The Bardhan et al (2020) model shows that the optimal allocation from their re-election point of view, is one where the allocation for a given program k to GP g is increasing in [Ca(g) $*$ Aa(g),g $*$ vkg] where Ca(g) denotes competitiveness of assembly constituency a(g) in which g is located, Aa(g),g $\in \{-1, 1\}$ is alignment of party controlling a(g) with party controlling GP g, and vkg is the marginal responsiveness of votes in GP g to program k budget. A GP with positive (resp. negative) alignment is controlled by the same (rival) party, hence allocating a larger budget to such a GP ensures an increase in

Table 8: Effect of Benefits on Votes for Incumbent in 2011 Straw Polls

Dependent Variable: Whether respondent voted for the incumbent party in majority at the GP				
	Poor Households		Marginally poor and Non-poor Households	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Private Benefits	0.036**	0.221**	0.011	0.141
	(0.014)	(0.095)	(0.013)	(0.104)
Public Benefits	0.011	-0.146	-0.024	-0.072
	(0.023)	(0.134)	(0.018)	(0.113)
Observations	891	891	1492	1492
Adjusted R^2	0.170	0.019	0.192	0.144
Mean Votes for Left	0.511	0.511	0.521	0.521
SD Votes for Left	0.500	0.500	0.500	0.500
F-Test of excluded instruments		7.83, 3.44		9.31, 5.35
(p-value)		(0.00, 0.00)		(0.00, 0.00)
Rank Test		7.65		6.18
(p-value)		(0.10)		(0.18)
Weak-Instrument-Robust AR test†		11.15		7.06
(p-value)		(0.05)		(0.22)

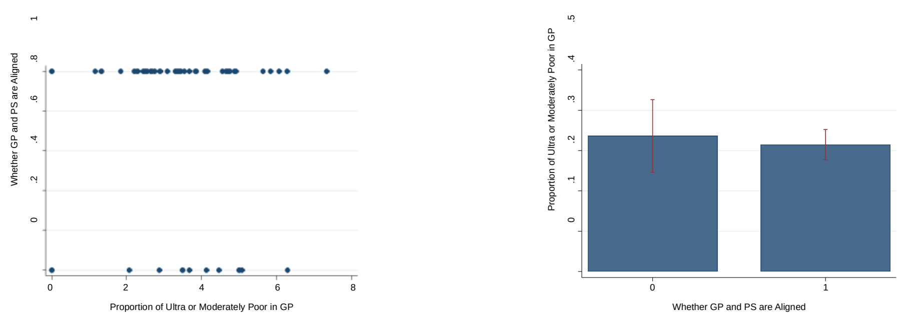
Note.- * p<0.10, ** p<0.05, *** p<0.01. † Ho: $\beta_{private}$=0 and β_{public}=0 and Ho: E(Zu)=0. The dependent variable is whether the respondent voted for the incumbent party in majority at the GP in our 2011 straw pools. Private and public benefits are standardized and aggregated over period 2009-2011. All specifications include household (HH) characteristics, GP characteristics, and district fixed effects. HH Characteristics include SC/ST, religion, landlessness, occupation, and level of education of household head. GP characteristics include dummy for left GP, dummy for left panchayat samiti (PS) and dummy for alignment between GP and PS. Robust standard errors are in parentheses, clustered at village level in (1) and (3).

votes for one’s own (resp. the rival) party in the electoral contest at the upper tier. Therefore the targeting is biased in favor of (resp. against) positively (resp. negatively) aligned GPs. The extent of such bias increases as the electoral contest becomes tighter, and marginal vote swings have a larger role in affecting which party wins. As poorer voters are more responsive, this factor by itself induces a pro-poor bias. Hence, a sufficient condition for across-GP targeting patterns to be progressive is that electoral competitiveness and alignment exhibit nonnegative correlation with with GP poverty rates.

Figure 3 examines the correlation between alignment (between control of GP and the next upper tier, the panchayat samity (PS)) and GP poverty. The scatter plot on the left shows the that all seven GPs which had a relatively higher number of poor households (more that 40) were all aligned GPs. However, the average proportion of poor households is very similar for aligned and non-aligned GPs, as shown in the bar graph on the right. Figure 4 plots the victory margin in 2011 assembly elections on the y-axis and number of ultra or moderately poor households on x-axis. The plots show that there is no relationship between GP poverty and electoral competition. Moreover, this lack of correlation does not differ significantly by GP-PS alignment versus non-alignment.

In summary, electoral competition and alignment did not vary with GP poverty rates. Hence the progressivity of across-GP budget allocations were primarily driven by a higher voting responsiveness of poor households to receipt of private benefits.

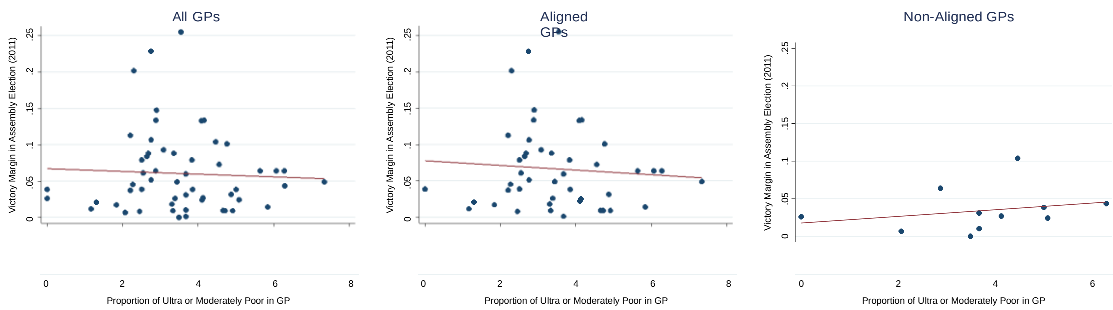
Figure 3: GP Poverty and Alignment



4.2 Targeting Implications of Formula Based Budgets

We now address the question of whether pro-poor targeting could have been improved upon using the formula recommended by the 3rd State Finance Commission (SFC) to allocate

Figure 4: GP Poverty, Electoral Competition, and Alignment



program grants to GPs. The SFC recommendations were based on the following GP variables, drawn from the village census and other household surveys:

GP1g : weighted population share of g, the sum of undifferentiated population (which receives a weight of 0.500) and SC/ST population (a weight of 0.098);
GP2g : female non-literates' share of g;
GP3g : food insecurity share of g, calculated from 12 proxy indicators collected in a 2005 Rural Household Survey, based on survey responses to questions such as "do you get less than one square meal per day for major part of the year?" ;
GP4g : population share of marginal workers, those employed less than 183 days of work in any of the four categories: cultivators, agricultural labour, household based economic activities and others;
GP5g : total population without drinking water or paved approach or power supply share of g;
GP6g : sparseness of population (inverse of population density) share of g.

Table 9 shows how well these characteristics predict the proportion of households in different poverty groups in any given GP. The ultra-poor ratio is rising in the SC/ST proportion and population sparseness, but did not significantly vary with the other SFC characteristics; the overall R-squared of this regression is 45%. So most of the variation in ultra-poor incidence is not explained. A larger fraction of variation (about two-thirds) in the moderately poor proportion is explained; most of this predictive power comes from a sharp positive slope with respect to village population size. The size of the other two groups is predicted less precisely (R-squared below 40%) by the SFC characteristics, with none of the individual characteristics being individually significant. These facts highlight the paucity of information available to construct formulae for programmatic GP budgets.

The specific formula recommended by the SFC for budget bg to be allocated to GP g is:

$$b_g = 0.598 * GP_{1g} + \sum_{i=2}^{4} 0.100 * GP_{ig} + \sum_{j=5}^{6} 0.051 * GP_{jg} \quad (1)$$

Table 9: Demographic Share of Poverty Groups and SCF GP Characterisitcs

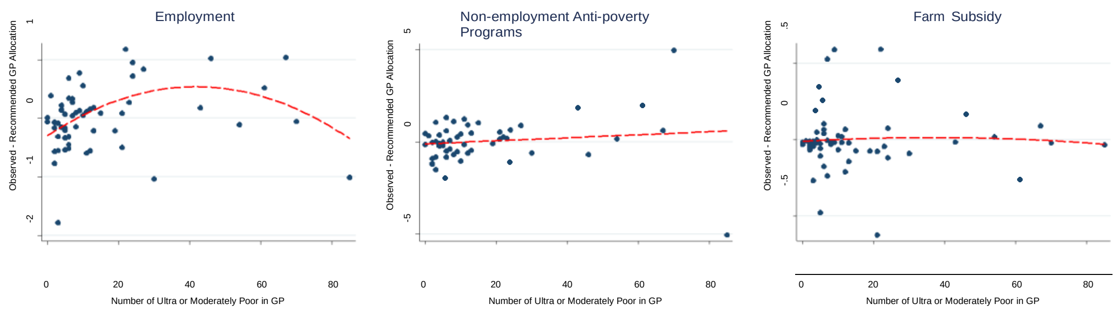
	Ultra Poor (1)	Moderately Poor (2)	Marginallly Poor (3)	Non-poor (4) (4)
Population	0.013	0.472**	0.042	0.172
	(0.111)	(0.178)	(0.790)	(0.836)
SC/ST	0.141**	0.021	-1.896	-2.086
	(0.063)	(0.143)	(1.450)	(1.489)
Female Illiteracy	-0.106	0.335	1.453	1.455
	(0.212)	(0.276)	(1.216)	(1.051)
Food Insecurity	-0.030	-0.054	-0.491	-0.109
	(0.042)	(0.090)	(0.315)	(0.331)
Lack of Infrastructure	-0.032	-0.230	0.881	0.469
	(0.239)	(0.344)	(1.533)	(1.406)
Marginal Workers	-0.029	-0.040	1.100	0.889
	(0.085)	(0.147)	(0.805)	(0.844)
Sparseness of Population	0.435**	0.266	0.409	0.707
	(0.180)	(0.229)	(0.706)	(0.885)
Observations	56	56	56	56
Adjusted R^2	0.449	0.649	0.387	0.333

Note: This table examines the relationship between our poverty measures and the components of the State Finance Commission formula. Observations are at GP level. Robust standard errors are in parentheses.

We apply this formula to calculate recommended budgets, upon assigning weights to GPs based on their scores using (1) and reallocating district program scales across these GPs in the same ratio as their respective weights. The deviation of the observed from the recommended GP budgets are plotted in Figure 5 against the proportion of (ultra or moderately) poor households within the GP. For non-linear relationships, we fit a quadratic regression whose predicted values are depicted by the red dashed line. Over the relevant range of GPs with less than 50% poor, we see that the regression for employment benefits is upward sloping. For other anti-poverty benefits, it is upward sloping over the entire range. Hence, the SFC recommended budgets for anti-poor programs were less progressive than the observed allocations. Evidently, political discretion of ULGs ended up creating a more pro-poor targeting pattern than was recommended by the SFC.

Next, using the within-GP targeting pattern estimates shown in Table 7, we predict the number of benefits each household would have received, had the observed GP budget been replaced by the SFC recommended budget, and the within-GP targeting pattern is described by the estimates in Table 7. There is no guarantee that the corresponding estimates of benefits

Figure 5: Deviation of Observed from SFC Recommended GP Budgets



received by each group generated independently for these groups will add up exactly to the incremental budget allocated. To ensure the GP budget remains balanced, we need to adjust the predicted benefits suitably. In one approach which we call proportional scaling, we scale the predicted benefits for all four groups by the same proportion in such a way to ensure budget balance. In the other method called residual scaling, we generate the estimates for the three poor groups independently from the within-GP targeting regression, and then adjust the benefits for the non-poor to ensure budget balance.

Under either method of scaling, we then aggregate the observed and predicted benefits from formula based grants across the entire sample, and compare the two for the average household in a given group. These results are shown in Figure 6. They confirm what one might expect from the greater progressivity of the observed GP budgets compared with the recommended ones — that the use of the SFC formula would not improve pro-poor targeting. Under proportional scaling, average targeting patterns are practically unchanged, while under residual scaling the poor would be worse off with formula based budgets.

The corresponding implications for a related but different measure of targeting — the aggregate share of benefits delivered to poor groups — are shown in Table 10. The SFC formula would increase the aggregate share of ultra poor and moderately poor households marginally for all three types of programs under proportional scaling. With residual scaling, on the other hand, targeting to all the poor groups would deteriorate for all welfare benefits.

The preceding exercise concerned the impacts of reallocating GP budgets within each district, but did not incorporate reallocations across districts. We now examine the consequences of reallocating across GPs using the SFC formula across the entire state. The predicted im- pacts (under the proportional scaling method) on per household benefits for each group are shown in Figure 7 and on the average group shares in Table 11. The effects turn out to be similar and somewhat larger compared to the corresponding impacts of within-district real

Figure 6: Comparing Observed Targeting with Predicted Targeting Under SFC- Formula-Based Within-District Reallocation of GP Budgets

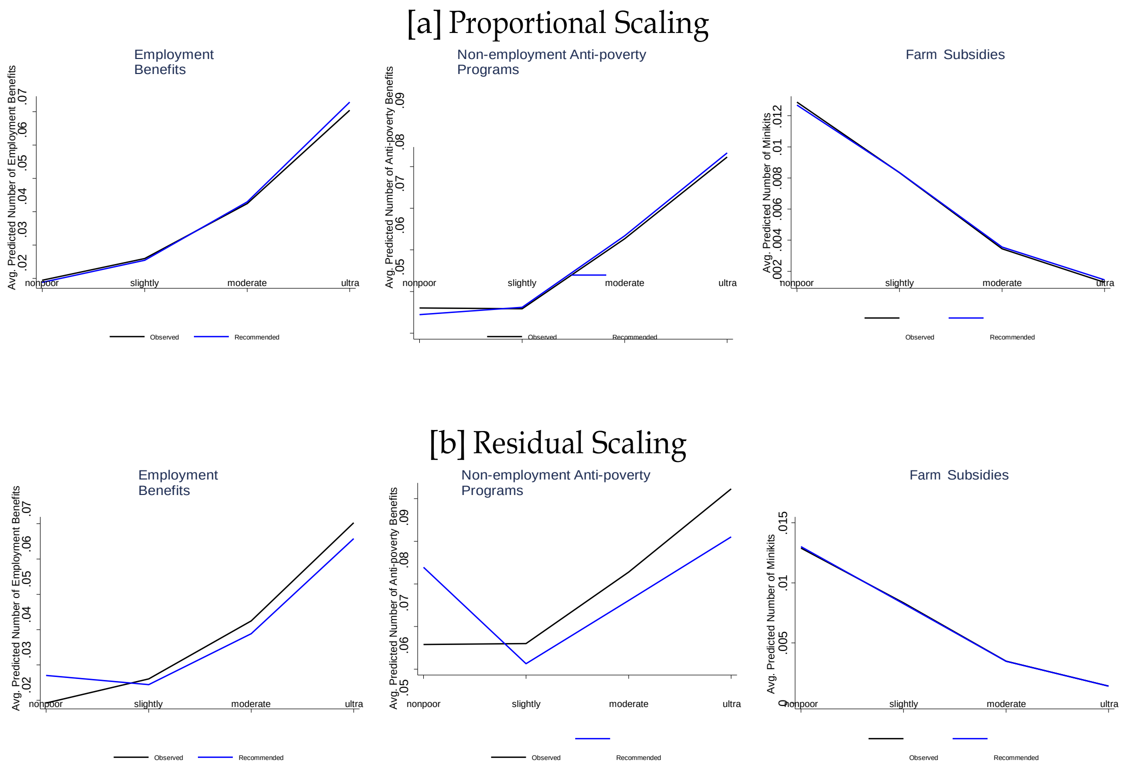


Table 10: Group Shares under Observed and Recommended Allocations with Within- District Formula-Based Reallocation

Group	Demographic Share	Employment Observed	Employment Rec.	Non-emp Anti-Pov. Observed	Non-emp Anti-Pov. Rec.	Farm Subsidy Observed	Farm Subsidy Rec.
[a] Proportional Scaling							
Ultra Poor	8.53	18.42	19.06	12.37	12.49	01.45	01.64
Moderately Poor	27.56	35.86	36.30	31.47	31.77	12.58	12.98
Marginally Poor	38.33	30.48	29.90	33.64	33.85	42.35	42.39
Non-poor	25.58	15.24	14.74	22.53	21.88	43.62	42.99
[b] Residual Scaling							
Ultra Poor	8.53	18.42	17.19	12.37	10.85	1.45	1.58
Moderately Poor	27.56	35.86	32.84	31.47	28.61	12.58	12.62
Marginally Poor	38.33	30.48	28.71	33.64	30.86	42.35	41.85
Non-poor	25.58	15.24	21.26	22.53	29.68	43.62	43.95

locations. For this reason, in the rest of the paper we focus on the effects of within-district reallocations.

Figure 7: Comparing Observed Targeting with Predicted Targeting Under SFC- Formula-Based State-wide Reallocation of GP Budgets, Proportional Scaling

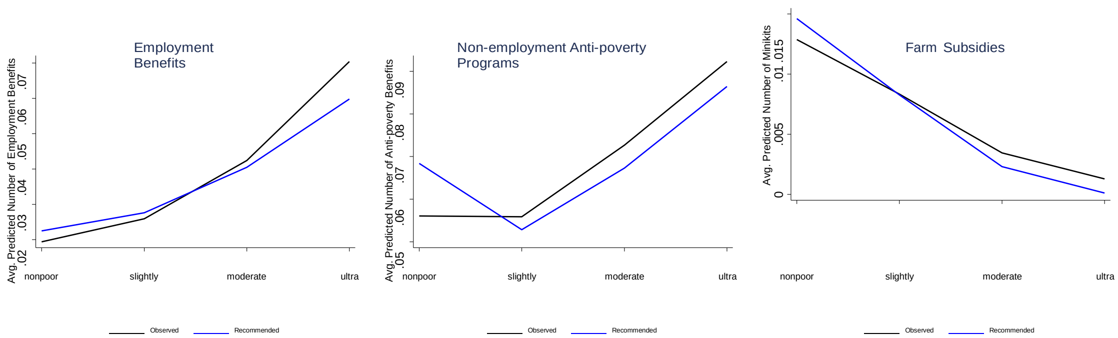


Table 11: Group Shares under Observed Allocation vs. Recommended Formula-Based State-wide Reallocation of GP Budgets, Proportional Scaling

Group	Demog. Share	Employment Observed	Employment Rec.	Non-emp Anti-Pov. Observed	Non-emp Anti-Pov. Rec.	Farm Subsidy Observed	Farm Subsidy Rec.
Ultra Poor	8.53	18.42	15.64	12.37	11.58	01.45	00.12
Moderately Poor	27.56	35.86	34.24	31.47	29.13	12.58	08.41
Marginally Poor	38.33	30.48	32.48	33.64	31.81	42.35	41.97
Non-poor	25.58	15.24	17.64	22.53	27.49	43.62	49.50

4.3 Alternative Formula Weights

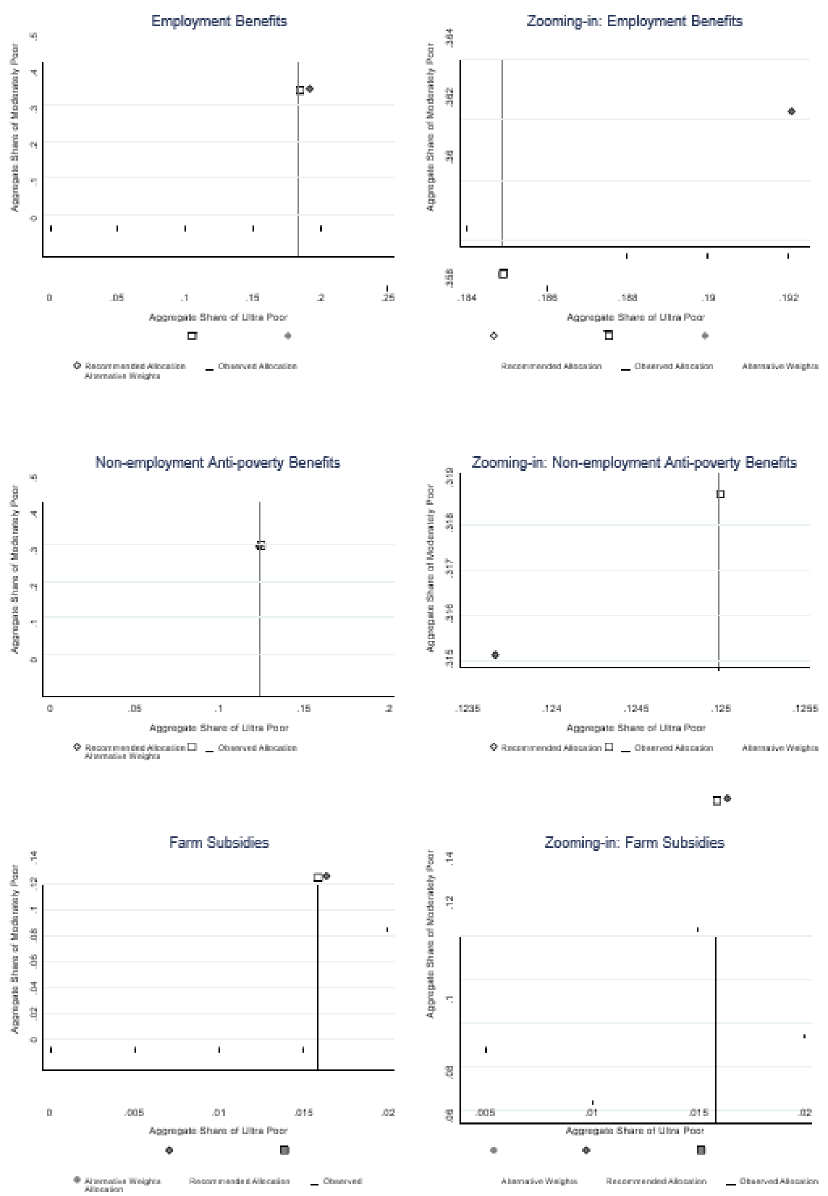
We now examine whether alternative formulae based on changing the weights on GP demographic variables used by the SFC can improve targeting of benefits to poorer groups compared to observed allocations. We consider within-district reallocations of GP budgets, where the set of GP characteristics used are the same as ones in equation 1. We draw 10,000 alter- native weights from the Dirichlet distribution using a likelihood model with uniform density

over each weight in the unit simplex defined by $\sum_i w_i = 1; w_i > 0$ in $\mathbb{R}^7$.

For each draw, we use proportional scaling to balance the budget, and calculate the aggregate share of benefits going to ultra poor and moderately poor households. Figure 8 plots the aggregate shares of the two groups implied by each alternative formula. The pair of aggregate shares associated with the observed household allocation are depicted by dashed lines. The horizontal and vertical lines depicting observed allocation partition the graph into four. The upper right quadrant depicts the set of weights where the aggregate share of benefits for both the ultra and moderately poor would be higher in the corresponding formula-based budget compared to the observed allocation.

The results show that formula based budgets with suitably chosen weights different can improve aggregate shares for the two poor groups compared to the observed allocation, but only marginally. These are depicted by the set of weights in the upper right quadrant of

Figure 8: Alternative Formula Weights and Aggregate Share of Poor Households



the graph. Figure 9 plots the predicted number of benefits for each poverty group if the formula weights had been chosen to maximize the average share of the ultra-poor group. However the quantitative improvement continues to be small. The ultra-poor group's share of employment and anti-poverty benefits increase from 18.4% to 19.2% and from 12.37 to 12.52% respectively.

Figure 9: Predicted Benefits for Alternative Weights that Maximize the Ultra Poor Share

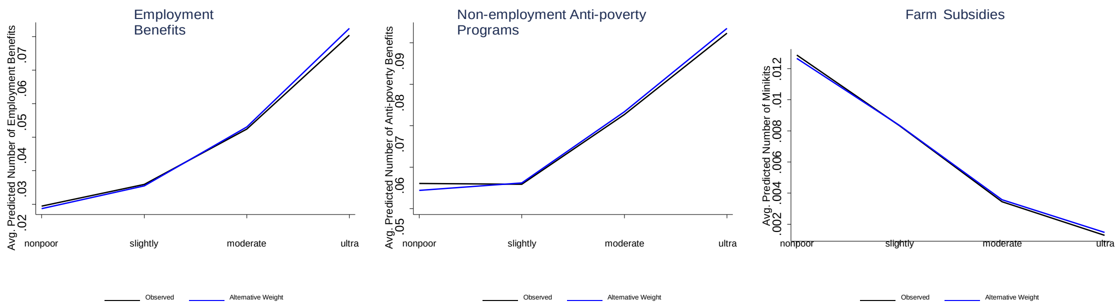


Table 12: Aggregate Shares under Observed and Alternative Allocations

Group	Demog. Share	Employment Observed	Employment Alt.	Non-emp Anti-Pov. Observed	Non-emp Anti-Pov. Alt.	Farm Subsidy Observed	Farm Subsidy Alt.
Ultra Poor	8.53	18.42	19.24	12.37	12.52	01.45	01.66
Moderately Poor	27.56	35.86	36.27	31.47	31.77	12.58	13.03
Marginally Poor	38.33	30.48	29.75	33.64	33.84	42.35	42.42
Non-poor	25.58	15.24	14.73	22.53	21.87	43.62	42.88

5 Conclusion

In summary, observed anti-poverty program targeting patterns were pro-poor, both within and across GPs in rural West Bengal. Switching to a rule-based financing system based on the State Finance Commission formula would have reduced the extent of pro-poor targeting. We show that alternative formulae obtained by varying weights on GP characteristics used in the SFC formula could improve pro-poor targeting only marginally. Hence, as long as formula based budgets are based on the kind of measures of village need used by the SFC, little improvement in pro-poor targeting can be expected.

The results highlight the need for more detailed criteria to be used by the state government or the SFC, in the event of a transition to centralized budgeting. Village demographics contained in the Census are unlikely to be precise enough, and need to be supplemented by more detailed measures of local poverty based on disaggregated household surveys. Moreover, these surveys could be used to estimate targeting patterns and the extent to which they differ across regions, which could also be used to fine-tune formulae used to determine budgets.

A number of qualifications are in order. We focused entirely on questions of vertical distributive equity in allocation of private benefits, and abstracted from many other welfare relevant dimensions. Politically manipulated variations in GP budgets result in horizontal inequity — unequal treatment of different GP areas in ways that cannot be defended on normative grounds, and reduce the legitimacy of incumbent parties. We ignored insurance considerations, i.e., responsiveness of allocations to need-based shocks either at the household or village level. Moreover, focusing on pro-poor targeting alone ignores possible under- provision of public goods and reduced political competition that has been alleged by many scholars to be pernicious consequences of clientelism. Assessing the empirical relevance of these concerns constitutes an important and challenging agenda for future research and policy experimentation.

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