A Sampling Strategy

The voter and sarpanch surveys sampled 96 gram panchayats in seven districts, twelve blocks and six of Rajasthan's seven administrative divisions.[1] As mentioned in the article, one GP President, or sarpanch, could not be interviewed, which yielded a sample of 95 sarpanch. The sample in this article was further reduced to 84 sarpanch on account of coding mistakes on the tokens measure made by our survey team.

The sample generalizes to voters and local politicians in rural contexts with a moderately high share of households below the poverty line and moderate inter-party competition. To build the sample frame for this population, we used 2001 census data on the rural composition of blocks,[2] data from the Government of Rajasthan on the share of below poverty line (BPL) households across blocks in 2001, and Election Commission data on political competition in panchayat samiti election– the tier of the panchayat raj system above the gram panchayat, which aligns with administrative blocks.[3]

We restricted the sample to blocks with a 75 percent rural population according to the 2001 census to reduce the chance of sampling GPs that function as suburbs, and excluded blocks with less than 20 percent of households in the BPL category in 2001 to ensure that the chance of sampling voters eligible for anti-poverty programs at random was non-trivial. This ensures that our sample is one of pervasive poverty and that the lottery benefit is salient in this population. We also excluded blocks where the median margin of victory across elections to all ward representative elections to the Panchayat Samiti– a sub-district, or block, level electoral body one tier above the GP– was greater

[1] Rajasthan has 33 districts, 249 blocks, 7 administrative divisions, and 9177 gram panchayats in all.

[2] Government data on the share of BPL households across gram panchayats was from 2001. More recent data was not available at the time of fieldwork in 2013.

[3] This is the lowest level of aggregation at which election commission data is available from a central source and the lowest level that permits party symbols on the ballot.

than 15 percent to increase the chance that we selected competitive GPs.[4]

After this restriction was applied, approximately 60 of 249 blocks were eligible for sampling in the state. Logistical concerns required that we sample two blocks in each district to the extent possible. This reduced the list to approximately 50 blocks. I randomly sampled one district in 5 of Rajasthan?s seven divisions from a pool of districts in which three or more blocks were eligible for sampling according to these criteria. Two blocks were randomly selected from the pool of eligible blocks in each district. In Udaipur, the sixth division selected, three eligible blocks did not exist in any one district; As a practical alternative, we randomly selected one block each from two neighboring districts in the division: Udaipur and Rajsamand.

Once 12 blocks were sampled, one of us collected data on political competition across gram panchayats through interviews.[5] Members of the research team interviewed block party presidents– party organizers immersed in the politics of gram panchayats in their block? who were asked to characterize the level of competition between Congress and the BJP as non-competitive, somewhat competitive, or very competitive. Of the 452 GPs in 12 sampled blocks, 180 were described as non-competitive, 133 as somewhat competitive, and 139 as very competitive. To increase the chance that the target population would be sampled, given resource constraints, non-competitive GPs were dropped from the pool for sampling. In each block, 4 GPs were randomly sampled among those coded as somewhat competitive and among those coded very competitive respectively.

Subsequently, one ward in each sampled GP (with an average of 100 households per

[4]Each member of this block-level legislative body is elected from one single ward and elected according to a first past the post electoral rule. We use the median margin of victory across ward elections to the Panchayat Samiti as gram panchayat electoral data could not be obtained during fieldwork.

[5]This was necessary because electoral commission data on gram panchayat elections is not available from a centralized source.

ward) were randomly sampled.[6] We randomly sampled household in sampled wards using the gram panchayat voters? list, which is public information provided by the Election Commission. We sampled (predominantly male) heads of household in randomly sampled households because they are generally the household member most engaged in village politics and citizen-state relations.[7] The elite survey was fielded the day after the vote survey was completed in a given GP.

[6]This was done according to the design of another article from this survey project which required that all sampled voters lived in one GP member's ward.

[7]To identify heads of household, interviewers were instructed to request to speak to the head of household upon approaching each sampled household. If heads of household were not at home, interviewers were instructors to either interview them in the fields in which many of them worked or to return to the household later in the day. If they did not return, supervisors provided alternative respondents who were also randomly selected from a voters list.

B Descriptive Statistics

Table 1: Voter Characteristics

Statistic	N	Mean	St. Dev.	Min	Max
Upper Caste	839	0.094	0.292	0	1
Rajput	839	0.105	0.307	0	1
Jat	839	0.105	0.307	0	1
Other Backward Caste	839	0.316	0.465	0	1
Scheduled Caste	839	0.167	0.373	0	1
Scheduled Tribe	839	0.068	0.252	0	1
Muslim	839	0.086	0.280	0	1
Illiterate	839	0.327	0.469	0	1
Some Primary School	839	0.230	0.421	0	1
Class 5 Pass	839	0.194	0.396	0	1
Class 8 Pass	839	0.138	0.345	0	1
Class 10 Pass	839	0.050	0.218	0	1
College Degree	839	0.089	0.285	0	1
Supporter	839	0.682	0.466	0	1
Co-Partisan	839	0.352	0.478	0	1

Table 2: Sarpanch Characteristics

Statistic	N	Mean	St. Dev.	Min	Max
Upper Caste	84	0.107	0.311	0	1
Rajput	84	0.155	0.364	0	1
Jat	84	0.083	0.278	0	1
Other Backward Caste	84	0.238	0.428	0	1
Scheduled Caste	84	0.202	0.404	0	1
Scheduled Tribe	84	0.048	0.214	0	1
Muslim	84	0.048	0.214	0	1
Illiterate	84	0.167	0.375	0	1
Some Primary School	84	0.226	0.421	0	1
Class 5 Pass	84	0.226	0.421	0	1
Class 8 Pass	84	0.143	0.352	0	1
Class 10 Pass	84	0.036	0.187	0	1
College Degree	84	0.202	0.404	0	1
Congress Member	84	0.619	0.489	0	1
BJP Member	84	0.333	0.474	0	1
Landless	84	0.167	0.375	0	1

C Regression Results

Table 3: Regression Results

	Dependent variable:			
	Expected Number of Tokens			
	(1)	(2)	(3)	(4)
Assets	-0.239^{*}	-0.212^{***}	-0.192^{***}	-0.192^{***}
	(0.140)	(0.068)	(0.065)	(0.068)
Supporter		1.091^{***}		
		(0.193)		
Supporter x Assets		0.165		
		(0.216)		
Non-Co-Partisan Supporter			0.928^{***}	0.904^{***}
			(0.195)	(0.194)
Co-Partisan Non-Supporter			-0.045	-0.057
			(0.287)	(0.286)
Co-Partisan Supporter			1.352^{***}	1.298^{***}
			(0.206)	(0.209)
Non-Co-Partisan Supporter x Assets				0.203
				(0.229)
Co-Partisan Non-Supporter x Assets				-0.408
				(0.339)
Co-Partisan Supporter x Assets				-0.075
				(0.237)
σ^2	3.353	0.674	0.620	0.589
Observations	839	839	839	839
Number of GP	84	84	84	84
pD	835.6	497.1	507.1	496.7
DIC	1947.5	1857.5	1872.0	1861.0
Note:				$^{*}\underline{\pi} < 0.1$; $^{**}\underline{\pi} < 0.05$; $^{***}\underline{\pi} < 0.01$

The regressions described above follow the protocol described in section 4. Results report estimates from a 3750 posterior simulations from a regression model estimated in a Bayesian framework through Markov Chain Monte Carlo (MCMC) with 3 chains and diffuse priors on all parameters, using the program `JAGS`. Standard deviations of the posteriors on the respective parameters are given in parentheses. Statistical significance in the model is given with respect to the posterior distribution. In particular, let $\widehat{\pi}$ be a vector of values drawn from the posterior distribution of a parameter of interest. Then, we define $\underline{\pi} = 2 * P(\widehat{\pi} < 0)$. The deviance information criterion (DIC) is a measure of fit that is defined as the sum of one-half of the estimated variance of deviance (pD) and the expected value of the deviance. The lower value of DIC is taken to be a better fit, with pD entering as a penalty for overfitting the data.

Table 4: Regression Results (continued)

	Dependent variable:			
	Expected Number of Tokens			
	(5)	(6)	(7)	(8)
Assets	-0.188^{***}	-0.201^{***}	-0.200^{***}	-0.193^{***}
	(0.067)	(0.065)	(0.064)	(0.069)
Non-Co-Ethnic Supporter	1.142^{***}	1.133^{***}		
	(0.206)	(0.212)		
Co-Ethnic Non-Supporter	0.412	0.458		
	(0.348)	(0.369)		
Co-Ethnic Supporter	1.307^{***}	1.331^{***}		
	(0.272)	(0.298)		
Non-Co-Ethnic Supporter x Assets		0.085		
		(0.222)		
Co-Ethnic Non-Supporter x Assets		0.107		
		(0.327)		
Co-Ethnic Supporter x Assets		0.291		
		(0.324)		
Co-Partisan Non-Co-Ethnic Non-Supporter			-0.029	-0.199
			(0.332)	(0.356)
Non-Co-Partisan Co-Ethnic Non-Supporter			0.503	0.390
			(0.353)	(0.375)
Co-Partisan Co-Ethnic Non-Supporter			0.641	0.436
			(0.526)	(0.554)
Non-Co-Partisan Non-Co-Ethnic Supporter			0.975^{***}	0.924^{***}
			(0.220)	(0.218)
Co-Partisan Non-Co-Ethnic Supporter			1.414^{***}	1.303^{***}
			(0.218)	(0.222)
Non-Co-Partisan Co-Ethnic Supporter			1.176^{***}	1.141^{***}
			(0.312)	(0.315)
Co-Partisan Co-Ethnic Supporter			1.670^{***}	1.604^{***}
			(0.353)	(0.350)
Co-Partisan Non-Co-Ethnic Non-Supporter x Assets				-0.452
				(0.394)
Non-Co-Partisan Co-Ethnic Non-Supporter x Assets				-0.069
				(0.392)
Co-Partisan Co-Ethnic Non-Supporter x Assets				-0.646
				(0.587)
Non-Co-Partisan Non-Co-Ethnic Supporter x Assets				0.152
				(0.235)
Co-Partisan Non-Co-Ethnic Supporter x Assets				-0.190
				(0.241)
Non-Co-Partisan Co-Ethnic Supporter x Assets				0.169
				(0.331)
Co-Partisan Co-Ethnic Supporter x Assets				-0.073
				(0.432)
σ^2	0.685	0.677	0.616	0.578
Observations	839	839	839	839
Number of GP	84	84	84	84
pD	520.9	514.7	456.8	535.0
DIC	1877.4	1871.5	1816.5	1901.2
Note:				$^{*}\underline{\pi} < 0.1$; $^{**}\underline{\pi} < 0.05$; $^{***}\underline{\pi} < 0.01$

The regressions described above follow the protocol described in section 4. Results report estimates from a 3750 posterior simulations from a regression model estimated in a Bayesian framework through Markov Chain Monte Carlo (MCMC) with 3 chains and diffuse priors on all parameters, using the program `JAGS`. Standard deviations of the posteriors on the respective parameters are given in parentheses. Statistical significance in the model is given with respect to the posterior distribution. In particular, let $\hat{\pi}$ be a vector of values drawn from the posterior distribution of a parameter of interest. Then, we define $\underline{\pi} = 2 * P(\hat{\pi} < 0)$. The deviance information criterion (DIC) is a measure of fit that is defined as the sum of one-half of the estimated variance of deviance (pD) and the expected value of the deviance. The lower value of DIC is taken to be a better fit, with pD entering as a penalty for overfitting the data.

D Robustness

D.1 Partisan and Gender Identity of the Sarpanch

While a large literature finds that local female leaders may display different political and distributional preferences – likely more pro-poor than male leaders (Duflo and Chattopadhyay, 2003), we find little evidence in our data. Recipients of tokens from male sarpanch were about 0.26 standard deviations below the mean wealth according to our asset measure, while recipients from female sarpanch were about 0.14 standard deviations below the mean. The difference was not statistically significant ($p = 0.36$). At first blush, it seems that the sarpanch with Congress Party affiliations are more pro-poor. Recipients of tokens from a Congress sarpanch were approximately 0.28 standard deviations below the mean, while recipients from non-Congress sarpanch were only 0.07 standard deviations below the mean (although the difference is not significant with $p = 0.12$). But this ignores, the "comparative" aspect of our claim. It turns out that Congress supporters are typically much poorer than non-Congress supporters, and conditioning on the relative wealth of co-partisans, Congress and non-Congress sarpanch both demonstrate pro-poor behavior. The average co-partisan of a Congress sarpanch is 0.17 standard deviations below mean GP wealth, and average co-partisan of a non-Congress sarpanch is 0.22 standard deviations *above* the mean GP wealth.

D.2 Ethnic Identity and Class Effects of the Sarpanch

Another competing hypothesis is that certain ethnic identities (measured as caste and religious identities of voters and sarpanch) and class identities (measured by education and land ownership) yield affinities to explain our results. Using a large set of predictors (and noting that variation in sarpanch effects enter as interactions in the regression), we show that magnitudes of our variables of interest (the asset wealth of the individual's household and co-partisanship) have similar magnitudes to our core models.

Table 5: Coefficients for Robustness Regression

Dependent Variable: Expected Number of Tokens

Assets	-0.199^{*}
	(0.121)
Supporter	1.285^{***}
	(0.271)
Assets x Supporter	0.100
	(0.214)
Rajput Voter	0.033
	(0.380)
Jat Voter	-0.340
	(0.378)
OBC Voter	-0.006
	(0.295)
SC Voter	-0.065
	(0.328)
ST Voter	0.257
	(0.440)
Muslim Voter	0.093
	(0.525)
Meena Voter	-0.006
	(0.495)
Literate Voter	-0.572
	(0.377)
Some Primary School Voter	0.594
	(0.381)
Class 5 Pass Voter	0.613
	(0.382)
Class 8 Pass Voter	0.722^{*}
	(0.386)
Class 10 Pass Voter	0.582
	(0.434)
σ^2	0.583

Assets x OBC Sarpanch	0.009
	(0.201)
Assets x SC Sarpanch	0.005
	(0.245)
Assets x ST Sarpanch	-0.418
	(0.414)
Assets x Muslim Sarpanch	0.254
	(0.466)
Assets x Meena Sarpanch	0.214
	(0.286)
Assets x Illiterate Sarpanch	0.151
	(0.267)
Assets x Landless Sarpanch	-0.076
	(0.253)
Supporter x OBC Sarpanch	-0.008
	(0.499)
Supporter x SC Sarpanch	-0.066
	(0.746)
Supporter x ST Sarpanch	-1.387
	(1.651)
Supporter x Muslim Sarpanch	-2.422^{***}
	(1.186)
Supporter x Meena Sarpanch	-0.277
	(0.651)
Supporter x Illiterate Sarpanch	0.326
	(0.832)
Supporter x Landless Sarpanch	-0.247
	(0.725)
Observations	839
Number of GP	84
pD	518.5
DIC	1892.1

Note: $^{*}\underline{\pi} < 0.1$; $^{**}\underline{\pi} < 0.05$; $^{***}\underline{\pi} < 0.01$

The regression described above follow the protocol described in section 4. The table on the left reports coefficients from voter-side variables, and the table on the right reports (interacted) coefficients by sarpanch characteristics. Results report estimates from a 3750 posterior simulations from a regression model estimated in a Bayesian framework through Markov Chain Monte Carlo (MCMC) with 3 chains and diffuse priors on all parameters, using the program `JAGS`. Standard deviations of the posteriors on the respective parameters are given in parentheses. Statistical significance in the model is given with respect to the posterior distribution. In particular, let $\widehat{\pi}$ be a vector of values drawn from the posterior distribution of a parameter of interest. Then, we define $\underline{\pi} = 2 * P(\widehat{\pi} < 0)$. The deviance information criterion (DIC) is a measure of fit that is defined as the sum of one-half of the estimated variance of deviance (pD) and the expected value of the deviance. The lower value of DIC is taken to be a better fit, with pD entering as a penalty for overfitting the data.

E The Role of Ethnicity

The effect of co-ethnicity on allocation is less pronounced than that of co-partisan supporters. Among non-supporters, a non-co-ethnic receives 0.20 tokens on average, while a co-ethnic receives 0.41 tokens on average. Among supporters, a non-co-ethnic receives 0.60 tokens on average, while a co-ethnic receives 0.68 tokens on average. Once again, in order to disentangle these effects from relative asset wealth, we calculate the impact of co-ethnicity on allocation through our modeling framework (Hypothesis H4).

Figure 1: Electoral Support and Co-Ethnicity

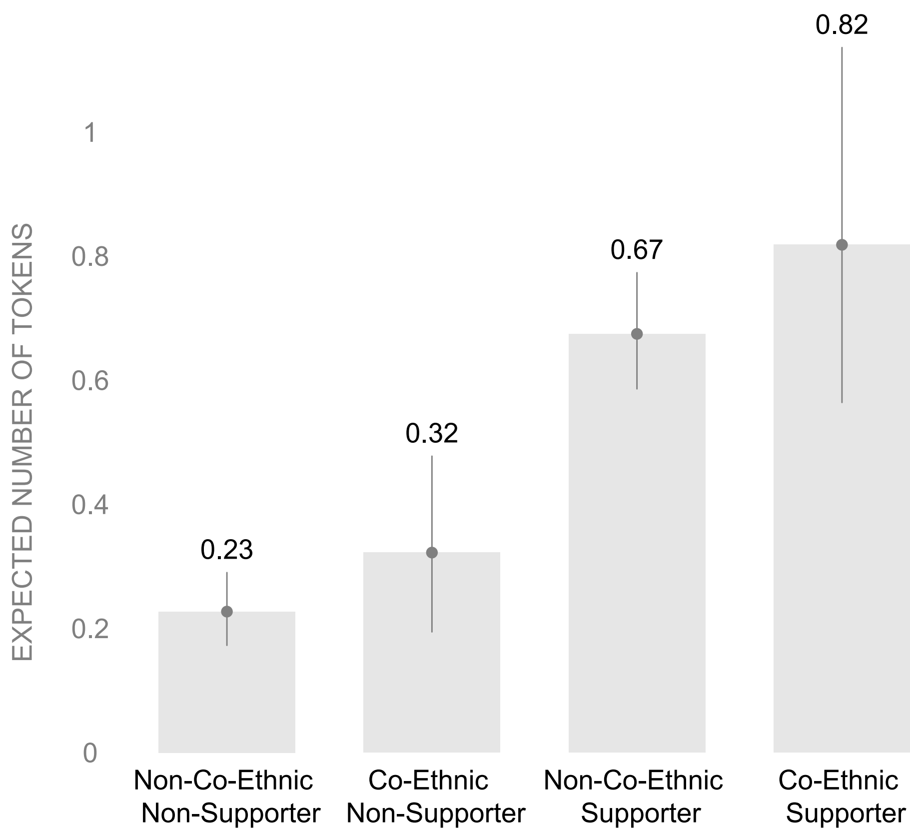


Figure 1, also in the main text, displays predicted average token allocation from a model that controls for relative asset wealth, political support, co-ethnicity, and the interactions between these variables, as displayed in column 6 of appendix C. The impact of co-ethnicity is statistically insignificant for both non-supporters and supporters, providing evidence for the assertion that elected leaders do not typically have preferences to narrowly focus on one ethnic group. This provides further support for the idea that minimum winning coalitions in multi-ethnic societies tend be built around political and partisan identities.[8]

[8]It is also worth noting that a very complicated model that interacts across political support, co-partisanship, co-ethnicity, and asset wealth, reported in column 8 of appendix C, finds a significant co-partisan effect among non-coethnics but not among co-ethnics. In these models, too, co-ethnicity is not a significant predictor.

F Relevant Code

F.1 Code for Item Response Model (Asset Index)

R Code:

```
N <- length(dat2$gpnumber[valid])

gp <- as.numeric(as.factor(dat2$gpnumber[valid]))
n.gp <- max(gp)
y <- cbind(pacca, scooter, bicycle, tv, toilet, fridge, fan, mobile, pump)[valid,]
K <- ncol(y)
item <- NULL; for (i in 1:K) item <- c(item, rep(i, N))
person <- rep(1:N, K)
y <- as.vector(y)
n <- length(y)


itr.data <- list("y", "n", "person", "item", "N", "K")
itr.inits <- function(){
list(a.raw=rnorm(N), b.raw=rnorm(K), sigma.person=runif(1,0,3),
sigma.item=runif(1,0,3), mu.a.raw=rnorm(1), mu.b.raw=rnorm(1))}
itr.par <- c("a", "b", "sigma.person", "sigma.item", "mu.b.raw")
itr.model2p <- jags(data=itr.data, inits=itr.inits, parameters.to.save=itr.par,
model.file="itemresponse2p.txt", n.iter=5000)

assets <- itr.model2p$BUGS$mean$a
```

JAGS Code – itemresponse2p.txt

```
model{
  for (i in 1:n){
    y[i] ~ dbern(p[i])
    logit(p[i]) <- mu[i]
    mu[i]  <- a[person[i]] - b[item[i]]
}
  for (i in 1:N){
    a.raw[i] ~ dnorm(0, tau.person)
    a[i] <- a.raw[i]
}
  for (i in 1:K){
    b.raw[i] ~ dnorm(mu.b.raw, tau.item)
    b[i] <- b.raw[i]
}
    mu.a.raw ~ dnorm(0,.0001)
    mu.b.raw ~ dnorm(0,.0001)
```

```
    tau.item <- pow(sigma.item, -1)
    tau.person <- pow(sigma.person, -1)
    sigma.person ~ dunif(0,100)
    sigma.item ~ dunif(0,100)
}
```

F.2 Code for Regression Model (> 1 predictor)

R Code

```
X <- as.matrix(Xadjmat[[i]])  ## GP-mean-adjusted matrix

y <- dat2$tokens_s[valid]

gp <- as.numeric(as.factor(dat2$gpnumber[valid]))
n.gp <- max(gp)
K <- ncol(X)
W <- diag(K)
n <- length(y)

cons <- rep(NA, length(gp))
for (i in 1:length(gp)){
con --s[i] <- 5/sum(gp == gp[i]) }

token.data <- list("y", "X", "W", "n", "gp", "n.gp", "K", "cons")
token.inits <- function(){
list(Tau.B=diag(K), mu.beta=rnorm(K), sigma.epsilon=runif(1,0,100))}
token.par <- c( "mu.beta", "B", "Sigma.B", "sigma.epsilon")
token.model <- jags(data=token.data, inits=token.inits,
parameters.to.save=token.par, model.file="qpoismultilevel.txt", n.iter=20000)
```

JAGS Code – qpoismultilevel.txt

```
model{
 for (i in 1:n){
     y[i] ~ dpois(lambda[i])
     log(lambda[i]) <- log(cons[i]) + X[i,] %*% B[gp[i],1:K] + epsilon[i]
     epsilon[i] ~ dnorm(0,tau.epsilon)
}
for (j in 1:n.gp){
B[j,1:K] ~ dmnorm(B.hat[j,], Tau.B[,])
B.hat[j,1:K] <- mu.beta[]
}
for (j in 1:K){
mu.beta[j] ~ dnorm(0,.0001)
}
```

```
Sigma.B[1:K,1:K] <- inverse(Tau.B[,])
Tau.B[1:K,1:K] ~ dwish(W[,], df)
df <- K+1
tau.epsilon <- pow(sigma.epsilon, -2)
sigma.epsilon ~ dunif(0,100)
}
```

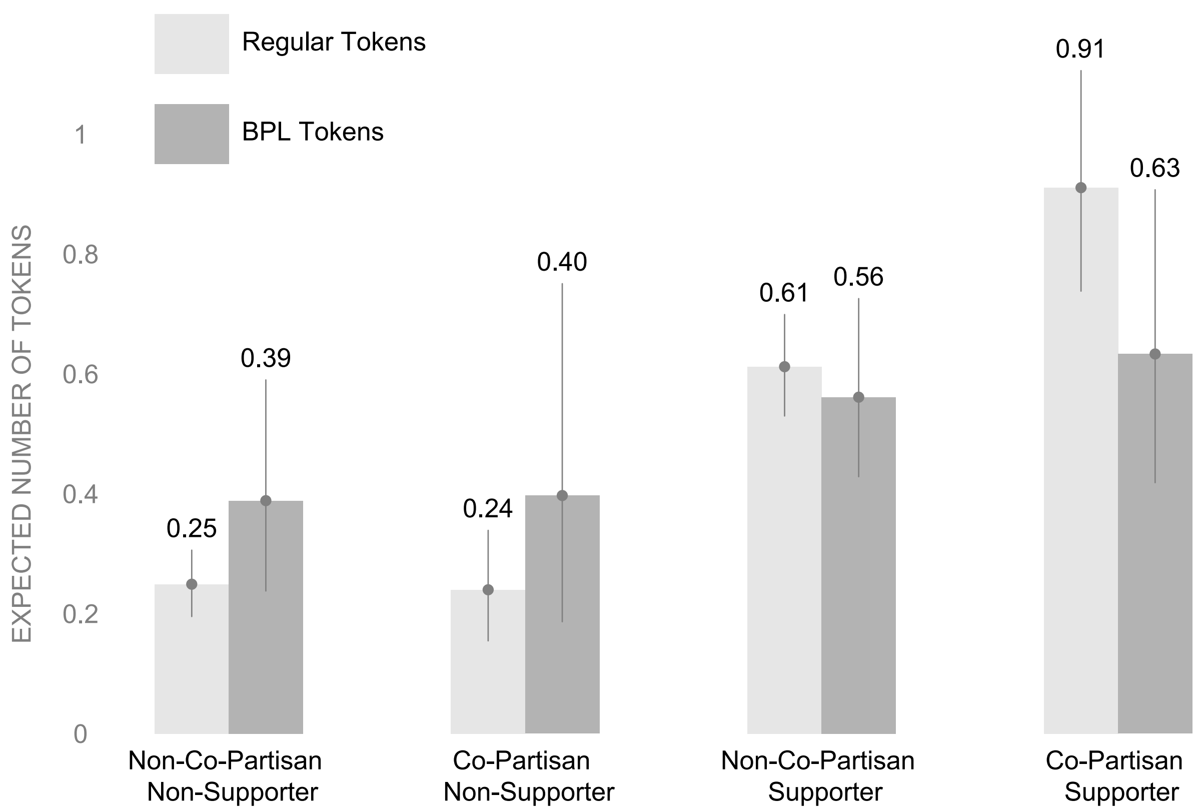
G Anti-Poverty Benefits

Our protocol was primarily geared towards understanding the underlying distributive preferences of sarpanch, which captures the targeting biases that local leaders will apply to the extent that they have discretion over everyday allocation. In weaker state capacity contexts, like in this study, these preferences likely have a relationship to behavior related to benefits with serious institutional constraints. In order to understand the role of personal preferences in distributive outcomes, we designed a "pro-poor cue." In this exercise, we asked the sarpanch to repeat the exercise above, but in a manner as if they were newly allocating below-poverty-line (BPL) benefits, i.e., welfare benefits in the Indian system. We also stipulated that no economic benefits would accrue to recipients of tokens in this exercise. This was done to remove discernible economic incentives for biased targeting. The pro-poor cue, thus, was designed to maximally remove biases from personal preferences in distribution in a weak state capacity scenario, but, as we will see below, such biases still persist in the data. While this may seem like a weak constraint, our results below demonstrate that this "pro-poor" cue has discernible effects on behavior, and observed behavior in this pro-poor cue exercise is quite related to actual distribution of benefits.

G.1 Political Biases under the "Pro-Poor" Cue

Figure 2 reports the estimated expected number of tokens for perceived electoral supporters and non-supporters without and with the pro-poor cue and further subdivides the effects by co-partisanship. As in the main text, under regular tokens the sarpanch believes the voter supported him in the last election, then he is willing to give significantly more tokens to that voter as compared to a non-supporter. When we further subdivide the results by whether the voter is a co-partisan of the sarpanch, we see more nuanced results. When there is no pro-poor cue, the sarpanch allocates more towards co-partisans; however, when we introduce a pro-poor cue, this co-partisan effect disappears, suggesting that the impact of sociopolitical ties are impacted by institutional constraints. Even in the case of the supporter effect, while the magnitude is large, the difference is not significant under a pro-poor cue.

Figure 2: Political Biases Comparison



G.2 Comparison to Actual Distribution

A natural concern is that our pro-poor cue is too disconnected from, and thus has little relevance for, the actual distribution of anti-poverty benefits. In order to understand the applicability of our measured preferences for actual distribution, we compared our lab behavior to the actual distribution of benefits. In particular, we focus our comparison on whether voters received two benefits, below poverty line (BPL) status and Indira

Awas Yojana (IAY) benefits. The first benefit entitles a household to purchase foodstuffs at a reduced price, and the second benefit entitles households to build a home using a government grant. There are only a small number of households that receive IAY benefits, and they must have BPL status to quality for these benefits. As such, the intended recipients of IAY benefits are particularly needy households that should be targeted more heavily. We verified receipt of a BPL card by asking respondents to show interviewers their ration cards. Although IAY benefits were self-reported, new homes built through this program can be visibly identified as beneficiaries.

Figure 3: Relation Between Lab Measures and Actual Distribution

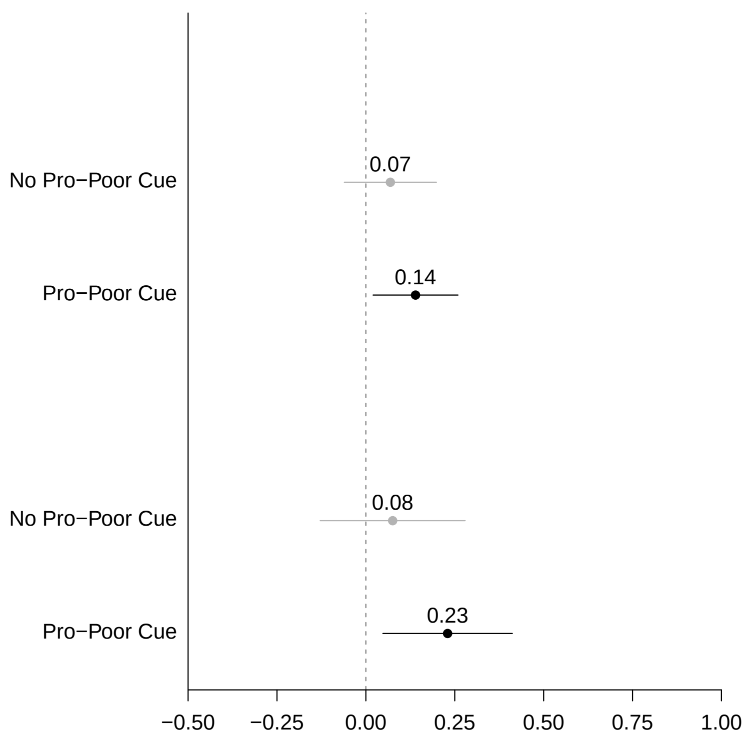


Figure 3 displays the coefficients of an overdispersed Poisson model, relating whether a voter has a benefit (BPL and/or IAY) and whether he or she received a token, using the regression formulation described above. While the coefficients are positive, when there is no pro-poor cue, voters do not receive significantly more tokens if they have a benefit. On the other hand, when there is a pro-poor cue, we find that voters who have benefits are also much more likely to receive a token, and the effects are significant. Consistent with the discussion above, the estimated coefficients are much larger for the IAY benefits than for BPL status. Having BPL status raises the expected number of tokens to a voter by 15% under the pro-poor cue, and receipt of IAY benefits raises the expected number of tokens to a voter by 26% under the pro-poor cue. This provides very strong evidence that our lab setup, when removing disincentives to allocate to the poor (i.e., institutional constraints), can be reasonably associated with actual distribution. Furthermore, we believe our basic setup, without a pro-poor cue, reasonably approximates underlying distributive preferences where the leaders are not constrained by the pressures of direct quid pro quo electoral motivations and have low social or institutional pressures to distribute benefits in a particular manner.