Declining Clientelism of Welfare Benefits? Targeting and Political Competition based Evidence from an Indian State*

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Abstract

It has been argued that since 2014, under the BJP-led central government, welfare benefits in India have become better targeted and less prone to clientelistic control by state and local governments. Arguably this has helped to increase the vote share of the BJP vis-a-vis regional parties. We test these hypotheses using longitudinal data from 3500 rural households in the state of West Bengal. We fail to find evidence that the new "central" programs introduced after 2014 were better targeted than traditional "state" programs, or that the targeting of state programs improved after 2014. Households receiving the new "central" benefits introduced since 2014 were more likely to switch their political support to the BJP. However, changes in the scale, composition or targeting of these programs, in clientelistic effectiveness of traditional state programs or in household incomes, fail to account for the large observed increase in the voters' support for the BJP. Non-Hindus, especially recent immigrant non-Hindus, were much less likely to switch support to the BJP, even after controlling for benefits received and changes in household incomes. Our results suggest that ideology and identity politics were more important factors explaining the rising popularity of the BJP.

Keywords: Welfare benefits, Clientelism, Targeting, Political competition, West Bengal

JEL Classification Numbers: H31, H42, H75, P16.

1 Introduction

Scholars have argued that in the course of economic development, welfare programs tend to become more programmatic and less prone to clientelistic manipulation by local intermediaries. This in turn improves the targeting of benefits and enhances political competition (Stokes, 2005, 2006, Kitschelt and Wilkinson, 2007, Bardhan and Mookherjee, 2020). In programmatic benefit schemes, entitlements are defined by formulae-based, publicly verifiable measures of deservingness. Benefits are delivered directly or through centralized mechanisms, with objective verification of transfers. All of this reduces the scope for local discretion, and the related diversion of benefits.

Historically, programmatic benefit delivery first became important in the US and UK during the spread of comprehensive social security and the welfare state between the 19th and first half of the 20th century. Many other developed countries have gone through a similar transformation. More recently, programmatic benefit delivery has become increasingly important in middle income countries such as Mexico and Brazil, and low income countries such as Indonesia and Pakistan. Research has shown that this has improved the accuracy of targeting, and increased political competition (de Jainvry et al., 2014, Larraguy et al., 2015, Frey, 2019, Banerjee et al., 2023, Haseeb and Vyborny, 2022).

It has been argued that a similar pattern has been emerging in India recently, especially since the Bharatiya Janata Party (BJP) was first elected with an absolute majority in the national parliament in 2014. Soon after assuming power, the BJP-led central government introduced new benefit programs such as the new "zero-balance" bank accounts (*Jan Dhan Yojana*), in-house toilets (*Swachh Bharat Yojana*), new methods of disbursing subsidies for LPG (cooking fuel – *Ujjwala Yojana*) and credit cards for farmers (*Kisan Credit Card*). These schemes are advertised as having more programmatic delivery mechanisms than traditional benefit programs, with eligibility based on clearly defined verifiable criteria, online verification, and electronic transfers. At the same time, since 2014 the central government has introduced new verification schemes through biometric cards and other electronic mechanisms for the beneficiaries of older welfare schemes such as the NREGS and public distribution system (PDS).[1] Scholars have argued this has reduced the scope for local discretion and corruption (Muralidharan et al., 2016, 2022, Banerjee et al., 2019). It is worth noting however, that in practice the implementation of all welfare schemes continues to involve substantial delegation to state and local government officials, both in the selection of actual beneficiaries and delivery of benefits.

Political support for the BJP has increased significantly between 2014 and 2019,

[1]This has coincided with a restriction in the funding for NREGS.

particularly in states where legislatures had previously been dominated by regional parties. Some scholars have argued that this shift can be attributed to the declining effectiveness of clientelism as traditionally practised via welfare schemes, the growing importance of economic and governance concerns in the minds of voters, and the central government's increased success at claiming credit for both the older schemes and the new welfare schemes introduced after 2014 (Deshpande et al., 2019, Wilkinson, 2021, Joshi et al., 2022). Other scholars have drawn attention instead to the broader rise of identity politics, the BJP's nationalistic ideology, its strong political organization, and Prime Minister Narendra Modi's personal brand image (Jaffrelot, 2019, Chhibber and Verma, 2019). Media accounts have reflected both viewpoints.[2]

This paper attempts to examine the validity of these hypotheses using data from the eastern state of West Bengal. West Bengal is a particularly interesting case to study. Many have argued that the dominance of Left-center parties in West Bengal since 1977 was connected to the systematic clientelistic distribution of traditional benefits, where local governments selectively delivered benefits to individuals who would reciprocate by voting for the political party in the subsequent election (Bardhan et al., 2015, 2021, Dey and Sen, 2020, Shenoy and Zimmerman, 2020, Mahadevan and Shenoy, 2023). Historically the BJP had little support in the state. However its vote share has increased dramatically in the recent past, from 6% in 2009 to over 40% in 2019. This provides a setting to examine whether the rise in the support for the BJP is the result of the mechanisms discussed above.

To do this, we use data from two waves of a longitudinal survey of 3500 rural households, conducted in 2013 and 2018 in two districts of West Bengal, immediately prior to the 2014 and 2019 parliamentary elections. The data allow us to examine how political attitudes, welfare benefits received, economic well-being and socio-economic status may have influenced how households voted in these elections. In particular, we use households' own reports of benefits received, and examine their association with various indicators of their socioeconomic status. This provides a more accurate depiction of actual targeting performance than administrative data. In our surveys we also asked households to participate in a confidential poll using a ballot that mimicked what they may see at a polling

[2] An article in the New York Times reporting on the outcome of four recent state elections states:

> Mr Modi, projecting himself as an ambitious champion of development as well as Hindu interests, also has a strong pull with voters across the country. His government has used the resources of the top-heavy and unequal Indian economy for well-targeted welfare schemes, handed out often in his name. In states where local BJP leaders were struggling in the elections, it was Mr Modi's face on the posters; the handouts for voters were presented as "Modi's guarantee". (New York Times Dec 4, 2023)

booth, to gauge their support for the different political parties.[3]

We first use the self-reports of receipt of various welfare benefits to examine whether the new "central" benefits were better targeted than traditional "state" benefits, and whether targeting of the state benefits improved after 2014. Here central benefits are defined as the new benefit schemes introduced after 2014 by the BJP-led central government, and state benefits are either pre-existing benefit schemes introduced by central or state governments before 2014, or new schemes explicitly introduced by the West Bengal state government after 2014.[4] To evaluate the progressivity of the benefit distribution, we examine the shares of benefits distributed across different groups, based on their ownership of cultivable land or their relative disadvantaged status (specifically we examine the shares going to Scheduled Castes (SCs) and Scheduled Tribes (STs)). We focus mainly on two new central schemes (in-house toilets and the LPG subsidy) and two traditional state schemes (NREGS and below-poverty-line, or BPL cards) since only the poor and disadvantaged (SC/ST) households are eligible for these benefits, and thus progressive distribution of the benefits was an explicit objective. Our data do not suggest clearly that the distribution of the central programs was always more progressive than that of the state programs during the period 2014–18, or that all state programs became more progressive after 2014. For instance, during 2014–18, across landholding categories, the LPG subsidy program was slightly more progressive than the BPL program, which in turn was more progressive than NREGS, while the in-house toilet program was the least progressive. The share of benefits goin to SC groups was highest for the LPG program, followed by BPL cards, in-house toilets and NREGS, in that order. Over time, we find that the NREGS program became more progressive while BPL became less progressive. Hence we fail to find evidence of consistent improvements in targeting.

We also examine the extent to which changes in the scale, composition, targeting and effectiveness of welfare programs can explain the increase in voters' support for the BJP and the decrease in support for the (incumbent) regional party the Trinamool Congress (TMC) between the 2013 and 2018 polls. We rely on a probabilistic voting framework where citizens' support for a political party depends on (*i*) utilitarian considerations affected by economic policies such as welfare benefits and perceptions of how policy choices affect their economic well-being, and (*ii*) a residual that incorporates the role of ideology, identity and supply-side factors such as organizational strength, advertising and media outreach of

[3]Similar approaches have been used by a number of researchers: see, for example Casey (2015) in Sierra Leone, Bardhan et al. (2021) in West Bengal and the Lokniti national election surveys all over India.

[4]In what follows, we use the terms "new benefits" and "central benefits" synonymously, and "traditional benefits" and "state benefits" synonymously.

the competing parties. The residual varies with household characteristics such as religion, caste and immigrant status, occupation, education and landownership. With retrospective voting, households' future expectations about political parties' policies are based on their recent observations and experiences. This generates a regression specification where the vote shares of the different parties in the straw poll from our survey can be explained by households' recent receipt of different welfare benefits, and a vector of household characteristics. We also compute the implications of these effects on the predicted change in vote shares for TMC and BJP. As the distribution of welfare benefits may be endogenously determined by voters' unobservable characteristics, we use a "leave out" shift-share instrument for a households' receipt of benefits. Specifically, we use time-invariant household characteristics interacted with per-household benefits received in other local government jurisdictions in the same district (Levitt and Snyder Jr, 1997, Bardhan et al., 2021) as the instrument.

Our main findings about the impacts of benefit programs on vote shares are as follows. First, we do not find evidence that state benefits were generally less effective at generating votes for the TMC in 2018 than in 2013. Receipt of an additional state benefit during the period 2014–2018 was associated with a 8.8 percent point *increase* in the likelihood that the household voted for the TMC in 2018; compared to a corresponding effect of 6.1 percentage points in 2013. Second, although the point estimate suggests that households that received the new central benefits were 6.6 percentage points more likely to vote for the BJP in 2018 than in 2013, this effect is not statistically significant. Third, the combined effect of changes in the scale of state and central benefits and their respective effectiveness at generating votes for either party predicts a net *decline* in the BJP vote share and an increase in the TMC vote share in 2018. In reality, actual vote shares moved in the opposite direction (a 5% decrease in the TMC vote share and an 18% increase in the BJP vote share). Thus the increased vote share of the BJP cannot be explained by the changing structure or effectiveness of benefit programs.

These results are robust to alternative specifications, such as allowing the effectiveness of benefits at generating votes to vary by local incumbent, to vary by the type of benefit program and with household characteristics. The empirical patterns remain similar even when we consider the changing composition and targeting patterns of state and central benefits. Analogous to Deshpande et al. (2019), we find that NREGS benefits became less effective at garnering votes for the regional party, the TMC after 2014. However, this coincided with an increased effectiveness of other state benefit programs, so that overall, state benefit program receipients became more likely to vote for the TMC than before.

These results mean that we must look elsewhere for explanations for the increased support for the BJP in West Bengal. We consider the possibility that households whose incomes have declined since 2014 voted against the incumbent TMC and generated the pro-BJP wave. However, using data on household income from employment and from the cultivation of the major cash crop in the area, we find no evidence that households whose incomes had declined after 2014 were more likely to vote for the BJP. The increase in the BJP's vote share between 2013 and 2018 was a fairly uniform 20–26 percentage points across landed households, irrespective of how much land they owned, although it increased by a smaller 14 percentage points among the landless. We also find no evidence to support the alternative claim that violence by TMC party activists during the 2018 village council (GP) elections that immediately preceded the 2019 parliamentary elections led to a wave of sentiment against the TMC. Instead, we find suggestive evidence that the support for BJP stems from its identity-based appeal to voters. In particular, Hindu households became more likely to vote for the BJP (and this increase is similar across Hindu native and Hindu migrant households). The vote share of the BJP increased by a relatively smaller 18% among scheduled tribe households, and a much smaller 9% among non-Hindus. None of the recent non-Hindu migrants in our sample expressed support for the BJP, either in 2013, or in 2018. These differences in its support by religion, caste and migrant status remain even after we control for other household characteristics, the welfare benefits they received and the changes in their economic circumstances. These results are consistent with Choudhary et al. (2020)'s claim based on all-India voters' data, that in 2019, demographic characteristics, caste and religious identity were the key predictors of support for BJP.[5]

This paper is organized as follows. Section 2 describes the data and presents selected descriptive statistics relating to household characteristics and welfare benefits (Sections 2.1.1 and 2.1.2) and compares targeting patterns across types of benefits and over time (Section 2.2). Section 3 describes the political context, details of the data relating to vote shares, and a range of descriptive facts relating to changes in voting patterns. Section 4 discusses the underlying voting model, tht regression specification and details of the IV strategy. Section 5 contains the main empirical results pertaining to impacts of benefit programs on vote shares, various robustness checks and alternative explanations. Section 6 concludes.

[5] Choudhary et al. (2020) draw a distinction with the 2014 parliamentary election, when, they argue, the BJP gathered support by striking an "issue-based electoral chord".

2 Data and Descriptive Statistics: Household Characteristics, Welfare Benefits and Targeting

2.1 Data and Descriptive Statistics

Our longitudinal survey data come from a sample of 3500 households residing in 72 randomly selected villages in the potato-growing *talukas* (sub-divisions) of the Hugli and Pashchhim Medinpur districts of West Bengal.[6] Panel A of Figure A1 shows the location of the two districts within the state and Panel B marks the locations of the sample villages. We analyse data from surveys conducted in 2013 and 2018. We collected extensive data on the households' demographic and socio-economic characteristics, transfers they received from the government and their engagement in civil society and political activities such as attending the village parliament *gram sabha*, and political rallies. There was no attrition in our sample across the two rounds and the same person within each household was the respondent in both rounds.[7]

2.1.1 Household Characteristics

In Table 1 we present statistics about the characteristics of our sample household. Only 5% of the households had female heads.[8] Seventeen percent of households report their head's religion as non-Hindu; the majority of these are Muslim. Just over a quarter of households report that the head belongs to the scheduled castes, and 4.8% report they belong to the scheduled tribes; the remaining 53% are general caste or other backward castes (OBCs). A very small fraction (0.2%) of respondents are recent migrants, specifically they reported that their household started residing in the village after 2003.

The majority of the households in our sample are of low socio-economic status. This is evidenced by their education levels and occupation, as well as their landholding and the construction of their dwellings. The median household head had not completed primary school. Nearly one-half of households report that the head's main occupation is cultivation, 28% of households report casual labour and 7% report business. Close to one-fifth of households do not own any agricultural land, and 63% own less than one acre. More than

[6]Sample villages were selected randomly from a stratified (by gram panchayat) list of villages, with the requirement that they be at least 8 kilometers apart from each other. The surveys were conducted for other unrelated projects: see Maitra et al. (2017), Mitra et al. (2018), Maitra et al. (2022, 2023b). As per the 2011 census of India, the population of Hugli was 3.4 million and the population of Pashchhim Medinipur was 5.2 million.

[7]While some households split, we tracked all households back to the original (parent) household.

[8]These are mainly widowed women.

Table 1: Selected Descriptive Statistics. Household Characteristics

	Survey		NSS†	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Male Headed Household	0.943	0.231	0.917	0.276
SC Household	0.255	0.436	0.248	0.432
ST Household	0.044	0.206	0.090	0.286
Non Hindu Household	0.173	0.378	0.154	0.361
General Caste/OBC Household	0.528	0.499	0.509	0.500
Recent Migrant Household	0.002	0.042		
Household Size	5.708	2.706	3.970	1.825
Household Head Married	0.901	0.299	0.911	0.285
Household Head: More than Primary Schooling	0.402	0.490	0.444	0.497
Household Head Occupation: Cultivator	0.487	0.500		
Household Head Occupation: Labour	0.279	0.448		
Household Head Occupation: Business	0.066	0.249		
Landless	0.187	0.390	0.100	0.300
Landholding 0–0.5 acres	0.377	0.485	0.739	0.439
Landholding 0.5–1 acres	0.222	0.416	0.101	0.302
Landholding > 1 acres	0.214	0.410	0.059	0.236
Lives in a Kuchha (non-permanent) House	0.552	0.497		
Change Employment Income	-0.213	1.610		
Experiencing Decline in Employment Income	0.660	0.474		
Change Potato Value-Added	0.255	0.489		
Experiencing Decline in Value-Added	0.093	0.290		

Notes: Employment income and Potato Value added in real terms (using the All India Price Index Number for Agricultural Labourer, General Index, 1986–87=100). Employment Income and Potato value added in Rs. ('0000). Change in employment income = Employment income (2018) – Employment income (2010–2013). Change in potato value-added = Potato value-added (2018) – Potato value-added (2010–2013). Decline in Employment income = Change in Employment income < 0. Decline in Potato value-added = Change in Potato value-added < 0. † : For NSS, pooled data from the rural sample of the 66^{th} and 68^{th} rounds (2009–2010 and 2011–2012 respectively) used from the districts of Hugli and Pashchim Medinipur (the two sample districts).

one-half live in non-permanent (or *kuchha*) dwellings, usually built of mud or tin. Our data also allows us to compute the proportion of households that experienced a fall in income between 2013 and 2018. Two-thirds of the sample households experienced a decline in employment income in this period, with an average drop of 21% in employment income. Fewer (9%) experienced a decline in earnings from potato cultivation (the leading cash crop in this region), while average potato earnings rose 25%.[9] Hence decline in employment income was the more important source of income decline.

[9] Employment income and potato value-added are in Rs. ('0000), calculated using detailed cultivation data collected through our survey, and then adjusted to real terms using the All India Price Index Number for Agricultural Labourer, General Index, 1986–87=100). Changes are calculated as the difference between the income in 2018 and the average income over 2010–2013. A negative change is coded as a decline.

To examine the representativeness of our sample, we compare our sample summary statistics with those from the National Sample Survey. In Columns 3 and 4 of Table 1 we present the corresponding averages using the pooled data from the rural sample in our two districts, from the 66^{th} and 68^{th} rounds of the National Sample Survey (NSS), conducted in 2009–2010 and 2011–2012 respectively. Note than unlike the NSS, our sample focused on the potato-growing areas in these two districts. Despite this, we find very similar proportions of scheduled castes, non-Hindus and general caste/OBC Hindus, and proportion of household heads that were married. However in our data there are fewer scheduled tribe households, the household size is larger and the distribution of landholding exhibits larger tails at both ends.[10]

2.1.2 State and Central Benefits

Of the new benefit schemes the BJP-led central government introduced after 2014, we focus on four programs that were publicized aggressively, and the advertisements for which prominently featured Mr Modi's image on billboards, television and social media. These include grants to construct in-house toilets (*Swachh Bharat Yojana*), free "zero-balance" bank accounts (*Jan Dhan Yojana*), direct transfers of subsidies for LPG cooking gas into beneficiaries' bank accounts (*Ujjwala Yojana*) and credit cards for farmers (*Kisan Credit Card*.)

Despite claims that these schemes had stronger safeguards against discretionary distortions by state and local governments and therefore better targeted to the intended beneficiaries (Deshpande et al., 2019, Wilkinson, 2021, Joshi et al., 2022), it is not *a priori* clear whether this is actually the case. This is because their last-mile implementation continued to involve state and local governments. All benefit schemes, old and new, are administered through a similar hierarchy of central, state and local officials, which includes both elected representatives and appointed bureaucrats at all levels. Financial and other approvals are granted by higher level bodies, and delivery is delegated to block (sub-district) councils, block development offices and village councils. Thus local officials have discretion over whether a household ultimately receives a benefit that it is eligible for.[11] For example, both the *Swachh Bharat* and *Ujjwala* schemes limit eligibility to households that are below the poverty line (BPL), and the BPL lists are created by local governments. Other eligi-

[10] Note that occupations were categorised differently in our survey than in the NSS data and so the occupational status variable cannot be compared.

[11] In practice restricted funds or staff shortages also typically make it difficult for local governments and service providers to satisfy all requests, so that benefits are rationed to households whom the local officials prioritize. Hence all schemes remain subject to local discretion, although some may be subject to greater oversight from higher level governments.

bility rules such as the requirement that beneficiaries should be poor or marginal farmers, disabled, pregnant mothers, or households with girl children etc., can only be verified by local governments. The *Ujjwala* subsidy is paid directly into bank accounts of beneficiaries; but in the *Swachh Bharat* scheme the state government can choose to deliver the benefit in the form of either cash or credit vouchers for construction materials.[12] Thus the ultimate delivery of the benefits follows very similar implementation models to the erstwhile "traditional" benefit schemes. Other programs such as Jan Dhan accounts and Kisan credit cards (among the new schemes, with only a few restrictions based on age and occupation) and NREGS (among the traditional schemes) were designed to be universal, and, in principle, available to all those who applied for them.

The new programs were advertised as more universal, better targeted and more efficiently administered than pre-existing welfare benefit programs. In addition, the aggressive branding of these schemes as attributable to Mr Modi personally could mean that voters clearly associated them with the BJP and Prime Minister Modi, and the BJP received more credit from voters for these schemes than the state-level incumbents received for the schemes they had previously introduced.

In what follows, the term "central benefits" refers to these four schemes, since we assume that voters attributed most of the credit for these benefits to the BJP. All other pre-existing welfare benefit schemes we consider pre-dated the 2014 BJP control of central government, and were distributed by the TMC led state government. As such it is plausible that recipients would continue to associate these programs with the TMC rather than the BJP, so we refer to them as "state" benefits. Households are coded as having received the state benefits if they report accessing work through the NREGS workfare program, having a below-poverty-line (BPL) ration card that entitles them to relatively larger quantities of subsidised food grains, sugar and kerosene, having a toilet constructed with funds from the village council, access to piped drinking water through the village council, medical help accessed with the help of the village council, housing construction funded through the state government's scheme (*Aawaas Yojana*), flood relief, and the conditional cash transfer for girls who delay marriage until the age of 18 (*Kanyashree*), also financed by the state government. Note that by construction, central benefits did not exist prior to 2014, while state benefits were distributed both before and after 2014.

In Panel A of Table 2 we see that the proportion of sample households that reported receiving (any) state benefits at least once during the two four-year periods of 2010–2013

[12] On the actual implementation of the Swachh Bharat program, the eligibility rules state: ... *States shall have the flexibility to decide on the implementation mechanism to be followed in the state.* (MDWS, 2014, page 12).

Table 2: Fraction of households who received central and state benefits in 2010–2013 and 2014–2018

	2010–2013 (1)	2014–2018 (2)	Difference (3 = 2 − 1)
Panel A: State Benefits			
Workfare scheme (NREGS)	0.523	0.455	-0.068***
	(0.500)	(0.498)	[0.012]
Below poverty line card	0.036	0.374	0.338***
	(0.187)	(0.484)	[0.009]
Toilet (village council)	0.060	0.206	0.146***
	(0.237)	(0.404)	[0.008]
Drinking Water (village council)	0.303	0.259	-0.044***
	(0.460)	(0.438)	[0.011]
Housing / House Construction	0.039	0.091	0.052***
	(0.194)	(0.287)	[0.006]
Flood Relief	0.125	0.143	0.018**
	(0.331)	(0.350)	[0.008]
Self-help group	0.047	0.142	0.095***
	(0.212)	(0.349)	[0.007]
Medical Help (village council)		-0.090	
		(0.286)	
CCT for delayed marriage (*Kanyashree*)		0.035	
		(0.185)	
Any State Benefit	0.749	0.762	0.013
	(0.434)	(0.426)	[0.010]
Panel B: Central Benefits			
In-house Toilets (*Swachh Bharat*)		0.155	
		(0.362)	
Bank accounts (*Jan Dhan*)		0.187	
		(0.390)	
LPG subsidy (*Ujjwala*)		0.161	
		(0.367)	
Kisan Credit Card		0.033	
		(0.180)	
Any Central Benefit		0.427	
		(0.495)	
Panel C: Number of Benefits Received			
State Benefits	1.170	1.795	0.625***
	(0.964)	(1.540)	[0.031]
Central Benefits		0.535	
		(0.698)	
All Benefits	1.170	2.330	1.160***
	(0.964)	(1.889)	[0.035]

Notes: As explained in the text, central benefits were not defined prior to 2014. For each benefit we report the average number of households that report receiving at the benefit at least once in the periods 2010–2013 (column 1) and 2014–2018 (column 2). "Any State Benefit" and "Any Central Benefit" denote the proportion of households that received at least one state (Panel A) or central (Panel B) benefit. Figures in parentheses denote standard deviations. Difference between mean 2013 and mean 2018. Figures in square brackets denote the standard error of the difference. Statistical significance of this difference computed using t-test. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

(column 1) and 2014–2018 (column 2). The difference (2018 — 2013) is presented in column 3. Panel B shows the proportion of households that reported receiving (any) central benefits at least once during 2014–2018. From 2010–2013 to 2014–2018, the proportion of sample households who reported they had received workfare through the NREGS decreased by 7 percentage points. This is consistent with the fact that the amount of funding available for the NREGS scheme decreased after 2014 (Jaffrelot, 2019). Similarly, the proportion of households who reported receiving drinking water through the local GP decreased by 5%. These results resemble findings of Deshpande et al. (2019) at the all-India level. However, for all other schemes, the fraction of beneficiaries rose. The increase was particularly striking for below-poverty line (BPL) cards: in the 2013 survey only 4% of households reported they had a BPL card, while in 2018, the corresponding proportion rose to 37% (p-value of difference = 0.00). Presumably these reports reflect receipt of new BPL cards; the substantial increase after 2013 was the result of a thorough revamping of BPL beneficiary lists that took place between 2013 and 2018. The proportion of households reporting that their community had a toilet built by the local government rose from 6 to 21% (p-value of difference = 0.00), while the proportion reporting they had received a housing benefit increased from 4 to 9% (p-value of difference = 0.00). There was an increase in the participation in women's self-help groups from 4 to 14% (p-value of difference = 0.00). Thus although the composition of benefits delivered changed, overall it continued to be the case that about 75% of households received at least one benefit (p-value of difference = 0.21). In comparison, only 43% of households reported they had received at least one new central benefit: this includes in-house toilets, bank accounts and the LPG subsidy (*Ujjwala*), each of which was reported by between 15 and 19% of sample households.

Thus, between the two time periods, central benefits were rolled out to slightly less than one-half of sample households, while the coverage of state benefits was substantially larger, with three out of four households receiving at least one state benefit. Despite its reduced coverage, the NREGS scheme continued to account for more beneficiaries than all four central schemes combined. The number of state benefits per household also increased, from 1.2 state benefits during 2010–13 to 1.8 in 2014–2018 (see Panel C of Table 2, p-value of difference = 0.00).

2.2 State and Central Benefits: Targeting

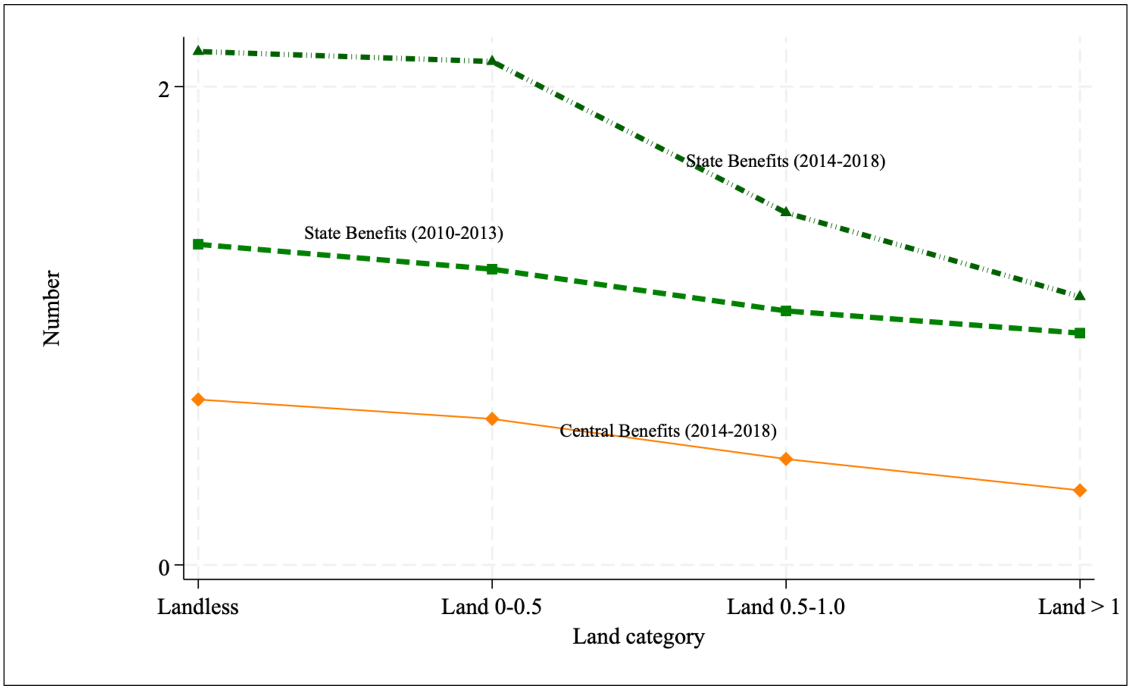
As we explained above, while most government welfare schemes are directed towards poorer and disadvantaged households, it is the state and local governments that are responsible for issuing the NREGS job cards and BPL cards that help to identify beneficiaries. In many schemes the state and local governments are also responsible for delivering the benefits, and among those holding the cards, ration the benefits to the households that satisfy a number of additional conditions. There are periodic attempts to reissue entitlement cards on the basis of information from new surveys and censuses (such as the 2011 Socio Economic and Caste Census). Central government-issued biometric identification (*Aadhar*) cards are also used to verify beneficiary status. Arguably these have resulted in improved targeting. Using the benefits reported by households in our survey and matching this with information regarding their socio-economic status, we now check whether the new central benefits were targeted better than the older state benefits, and whether targeting of the state benefits improved after 2013.

To assess a household's economic status, we use data on their ownership of cultivable land as a proxy of their wealth. We categorize households into four landholding categories: landless, and those owning 0–0.5 acres, 0.5–1.0 acres and > 1.0 acres respectively. In our sample 19% of households are landless, while 39%, 22% and 17% of households have landholding 0–0.5 acres, 0.5–1.0 acres and > 1.0 acres respectively. Panel A of Table A1 in the Appendix presents selected descriptive statistics by landholding cateory and shows that landholding correlates positively with education, assets, income and farming occupation of the head. The percentage of landless households where the head has less than primary school is almost 80 (compared to 35 for households with more than 1 acre of land); 62% of landless households reside in a *kuchha* house (compared to 43% for households owning more than 1 acre of land); 13% of household heads of landless household report cultivation as their main occupation (compared to 73% for households with than 1 acre of land). Over the period 2010–13, the average household income for households with more than 1 acre of landholding was nearly double that of landless households (Rs. 84328 vs Rs. 39747).[13]

Figure 1 plots average number of state and central benefits received per household across the four land categories. In absolute terms, households received more benefits from state schemes than central schemes, reflecting simply the larger number of state schemes

[13]We check robustness to an alternative proxy where households are classified into different quantiles of predicted income where these predictions are based on household assets and demographic characteristics. We regress average total household income during the period 2010–2013 on indicator variables for landlessness, living in a *kuchcha* house; female household head, head with less than primary schooling, and head primarily occupied in casual labour. Table A2 in the Appendix presents the results from this regression. We report separately results with and without village fixed effects. As expected, landless households, those living in a *kuchcha* house, with less-educated household heads and those whose primary occupation is casual labour are predicted to have lower household income. We then classify households into four different quartiles (Q1–Q4, with Q1 denoting the poorest households) on the basis of their predicted household income. The results presented in Figure A2 are very similar to the patterns in Figure 1. and show that households in higher quartiles were less likely to receive benefits, indicating that benefits were progressively distributed overall.

Figure 1: Number of Central and State Benefits Received by Land category



that existed in both time periods and their availability to households. As evidenced by the negative slope, in both sets of schemes and in both time periods, poorer groups received more benefits. However, during 2014–18, there was a change in this slope for state benefit schemes, such that the two poorest groups received substantially more benefits (more than 2 benefits per household) than the relatively better-off groups.

To compare the progressivity of these schemes, it is preferable to estimate the implied benefit shares of the poorer groups (as is standard in the literature, see for example Lanjouw and Ravallion, 1999, Alderman, 2001, Biggs et al., 2009, Kakwani et al., 2021). It is also more informative to focus on those particular schemes where the benefits were intended exclusively for the poor and disadvantaged: among the central schemes these include only the toilet and LPG subsidies.[14]

In Table 3, Panel A present the results of OLS regression of the likelihood that a household received a benefit (estimated separately for in-house toilets, LPG subsidy, NREGS employment and BPL cards) on land category. The omitted category is households with more than 1 acre of land. Panel B present the implied (cumulative) benefit shares of households owning below the specified cultivable landholding size (omitted category:

[14]All households were eligible for Jan Dhan accounts, and all farmers were eligible for Kisan (farmer) credit cards. Table A3 in the Appendix reflects this non-progressivity of these schemes: the probability that households with more than 1 acre of land had Jan Dhan accounts or farmer credit cards is higher than for the other four benefits.

Table 3: Targeting of State and Central Benefits. Likelihood of Receiving Benefits of each Type by Land category

	Central Benefits 2014–2018		**State Benefits 2014–2018**		**State Benefits 2010–2013**	
	In-House Toilet	LPG Subsidy	NREGS Employment	BPL Card	NREGS Employment	BPL Card
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Likelihood of Receiving*						
Landless	0.091***	0.230***	0.370***	0.489***	0.109***	0.065***
	(0.026)	(0.026)	(0.037)	(0.039)	(0.037)	(0.014)
Landholding 0—0.5 acres	0.117***	0.153***	0.259***	0.330***	0.078***	0.035***
	(0.022)	(0.023)	(0.033)	(0.034)	(0.028)	(0.010)
Landholding 0.5—1.0 acres	0.046**	0.061***	0.135***	0.124***	0.048*	0.013**
	(0.018)	(0.014)	(0.025)	(0.026)	(0.026)	(0.006)
Constant	0.080***	0.041***	0.248***	0.119***	0.459***	0.006**
	(0.017)	(0.008)	(0.033)	(0.025)	(0.033)	(0.003)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.015	0.045	0.060	0.121	0.005	0.014
Panel B: *Cumulative Proportion of Benefit Accruing*						
Landless	0.214	0.328	0.265	0.316	0.212	0.386
Landholding Up to 0.5 acres	0.723	0.810	0.710	0.795	0.622	0.843
Landholding Up to 1.0 acres	0.909	0.956	0.904	0.944	0.845	0.969

Notes: OLS regression results presented. Panel B present the implied (cumulative) benefit shares of households owning below the specified cultivable landholding size (omitted category: households with landholding > 1.0 acres), where the benefit share of land category j is calculated by $\frac{\omega_j \gamma_j}{\sum_j \omega_j \gamma_j}$, where γ_j denotes the estimated likelihood of receiving the benefit by a household in land category j and ω_j is the proportion of sample households in land category j. We then aggregate over all categories up to j we obtain the cumulative benefit shares. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

households with landholding > 1.0 acres). Note that the implied share of the benefits that go to any particular category is calculated by weighting the predicted likelihood that a household in this category receives the benefit, by its share in the population.[15]

With one exception, for each pair-wise comparison of schemes there is an unambigous ranking of progressivity. During 2014–18, the LPG scheme was the most progressive (only 4.4% of the benefits accrue to households with > 1.0 acres of landholding). The BPL card scheme was less progressive, followed by the NREGS workfare program, and then in-house toilets.[16]

Overall thre is no evidence that central welfare schemes are more or less progressive

[15]Specifically, the benefit share of land category j is calculated by $\frac{\omega_j \gamma_j}{\sum_j \omega_j \gamma_j}$, where γ_j denotes the predicted likelihood that a household in land category j receives the benefit, and ω_j is the fraction of sample households that belong to land category j. By aggregating over all categories up to j we obtain the cumulative benefit shares.

[16]The exception is that during 2014–18, the landless had a larger share in the NREGS workfare than in the in-house toilet scheme (26.5% v. 21.4%), but those with less than 0.5 acres had a slightly smaller share in the NREGS workfare than the in-house toilet scheme (71% v. 72.3%), and this is also true for households with less than 1 acre of land (90.4% v. 90.9%). Thus if anything the NREGS appears to be slightly more progressive, although the difference is too small to be substantial.

Table 4: State and Central Benefits Shares, by Social Group

	Central Benefits 2014–2018		**State Benefits 2014–2018**		**State Benefits 2010–2013**		Share of
	In-House Toilet	LPG Subsidy	NREGS Employment	BPL Card	NREGS Employment	BPL Card	Population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ST Households	0.246	0.257	0.683	0.707	0.545	0.120	0.048
	[0.010]	[0.012]	[0.010]	[0.014]	[0.006]	[0.025]	
SC Households	0.251	0.329	0.667	0.589	0.547	0.059	0.264
	[0.325]	[0.459]	[0.289]	[0.358]	[0.194]	[0.375]	
Non Hindu Households	0.083	0.104	0.288	0.438	0.480	0.025	0.163
	[0.041]	[0.055]	[0.047]	[0.101]	[0.065]	[0.060]	
Other Households	0.121	0.085	0.379	0.217	0.522	0.021	0.526
	[0.623]	[0.474]	[0.654]	[0.526]	[0.736]	[0.540]	

Notes: Proportion of Households with identity j receiveing each benefit provided. The terms in the square brackets present the weighted proportion of benefits accruing to household of identity j and is given by $\frac{\omega_j \gamma_j}{\sum_j \omega_j \gamma_j}$ where γ_j is the raw proportion of benefits accruing to household with identity j and ω_j is the proportion of sample households with identity j (column 8).

than state welfare schemes. Similarly, there is no clear evidence that welfare schemes became more progressive after 2014: the BPL program became less progressive between 2010–13 and 2014–18, but the NREGS scheme became more progressive.[17]

Finally, we examine the benefit shares of the disadvantaged minorities such as the scheduled caste and scheduled tribe households. As Panel B of Table A1 in the Appendix shows, ST and SC households had on average the least education, greatest likelihood of living in a kuchha house, and were more likely to be landless and to be working in manual labour (and therefore less likely to state own cultivation as their main occupation). Table 4 shows the fraction of each group that received the different benefits, with implied (population share weighted) benefit shares shown in square brackets below each entry. During 2014–18, STs received very similar shares in all four schemes, while SCs' share was highest for the LPG subsidy, followed by BPL cards, in-house toilets and NREGS in that order. For non-Hindus, their share was highest in BPL cards, followed by LPG subsidy, NREGS and finally in-house toilets. Within state programs, the shares of SCs and STs in BPL fell after 2014, while NREGS shares improved. The non-Hindu share in BPL cards rose after 2014, but in NREGS fell. As in the case of progressivity by land status, no clear ranking emerges between central and state programs, or of state programs before and after 2014.

Thus, despite the fact that the new central welfare programs have been billed as

[17] In Table A4 in the Appendix we present results from same exercise using predicted income quantile of households (as discussed in footnote 13). We find that during 2014–2018, the LPG subsidy scheme continued to be the most progressive, and that BPL and in-house toilets could not be compared against each other, but both more progressive than NREGS. If instead we focus only on the share of benefits held by the landless, then the BPL card scheme was more progressive than in-house toilets. Once again there is no clear ranking of state and central programs. Similarly, between 2014–18 and 2010–13, the BPL scheme became less progressive while NREGS became more progressive.

more progressive and better targeted (more programmatic), the data do not support these claims. This is likely because these schemes continue to rely on indicators for eligibility and transfer mechanisms where local discretionary elements have a role.

3 Political Context and Vote Shares

3.1 Background: Political Competition in West Bengal

For over three decades starting in 1977, West Bengal's state legislature was dominated by the Left Front, a coalition of left leaning parties led by the Communist Party of India (Marxist), or the CPI(M). The Left Front secured an absolute majority in each election that took place between 1977 and 2011, both in the state legislative assembly, and in the national parliamentary seats from the state. The Indian National Congress (INC) was the largest opposition party in the state until 1997, when Mamata Banerjee, a veteran INC member broke away to form the *Trinamool* (grass roots) Congress (henceforth, TMC). The TMC often formed election-time alliances with the Indian National Congress to fight the CPI(M). In 2011 the CPI(M) lost control over the state legislature for the first time since 1977, when the TMC came to power. The TMC also won the subsequent 2016 state assembly elections. They also won the majority of seats and the highest vote share in the state, in both the 2009 and 2014 parliamentary elections (see Figure A3 in the Appendix). TMC therefore was the state incumbent both in the 2014 and the 2019 parliamentary elections.

The BJP was a minor player throughout this 35-year period. During the 2009 national elections, it received only 6% of the vote share and won one of the 42 parliamentary seats in West Bengal (see Figure A3). In the 2014 parliamentary elections its vote share increased to 17% and it won two seats. In the 2019 parliamentary elections its vote share increased dramatically to over 40%, and it won 18 seats, making it the second-most important political party in West Bengal. Although the TMC won the majority of the parliamentary seats in 2019, its vote share did not change much from 2014. This would suggest that the BJP's vote share increased mainly at the expense of the Left Front, whose vote share decreased from 30% in 2014 to below 10% in 2019.[18] However, when we compare all three election years, we see that this movement took place in two steps: support shifted from the Left

[18]Figure A4, in the Appendix, presents a map of the parliamentary constituencies in West Bengal. It shows how voter support for the TMC, BJP and the Left Front changed over the period 2009 to 2019. It is clear that it was the areas where the Left Front was dominant in 2009 where the BJP received the larger vote shares in 2019. Many political commentators have referred to this change as *Baam theke Ram* ([movement] from the Left to Ram, the Hindu God).

Front to the TMC in 2014, and then from the TMC to BJP in 2019. The longitudinal household data we discuss below indicate more complex shifts at play, e.g., equally large flows of voter support from the Left to the TMC as from the TMC to BJP.

This increase in the support for the BJP in West Bengal in 2019 occurred against a backdrop of increasing vote share for the BJP across India, although the increase has been more dramatic in West Bengal. Whereas the BJP's vote share in West Bengal was below 10% until 2009, it was around 20% in the country as a whole. Between 2009 and 2014 it increased by about 10 percentage points both in West Bengal and India, and then between 2014 and 2019 it increased by 23 percentage points in West Bengal and by 7 percentage points in India. The corresponding contrast between West Bengal and the country as a whole in the evolution of seat shares was even more drastic.

3.1.1 Vote Shares: Survey Data

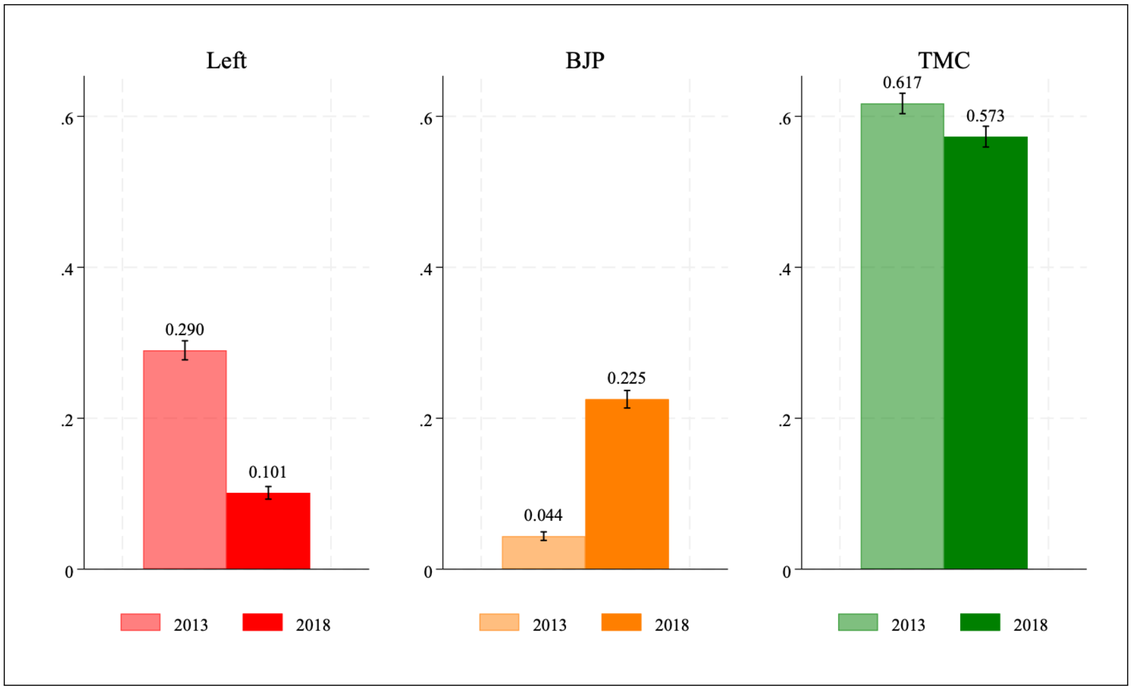
Our data on political support for the different parties comes from data collected using straw polls (both in 2013 and 2018) where respondents cast a simulated "secret ballot" or straw poll for the political party they supported.[19]

Figure 2 presents the vote shares of the Left Front, BJP and TMC from these straw polls, plotted separately for 2013 and 2018. In line with the pattern in West Bengal as a whole, we see a decrease in the vote share of the Left Front, and an increase in the vote share of the BJP. In particular, the Left Front's share dropped from 29% to 10%, there was a smaller decrease in the vote share of TMC from 61.6% to 57.3%, and the BJP's vote share increased from 4.4% to 22.5%. This 18 percentage point increase in the BJP's vote share in our survey data is in the same direction as, although smaller than what we see in publicly available data from the actual elections in 2014 and 2019, from polling booths in our sample villages (where the BJP's vote share increased by 35%), in the districts where the villages are located (31%), and in West Bengal more broadly (23%).[20] Although the magnitudes of changes differ, the survey data indicate the same qualitative changes we saw

[19] The households were assured that their votes would remain confidential, and that participation in the exercise was voluntary. Those who agreed were given the ballot paper and a locked box containing ballots cast by other respondents previously, as well as some dummy ballots. The ballots contained no identifying information except the household code number assigned by the PIs that was not known to interviewers or respondents, and that data entry operators could not link back to the households. After they marked the symbol of their preferred political party, respondents folded and placed the ballot in the locked box, and shook it to mix the ballots before returning the box to the interviewer. All households in our sample consented to participate in the straw ballot in 2013; the proportion who selected the option *None of the Above* on the ballot was less than 1%. In 2018, 8.1% of households refused to participate in the straw poll and 1.2% of the sample who participated voted *None of the Above*. However, refusal to participate in 2018 was uncorrelated with the party they voted for in 2013.

[20] These comparisons are represented visually in Figure A5 in the Appendix.

Figure 2: Poll Vote Shares. Survey Data



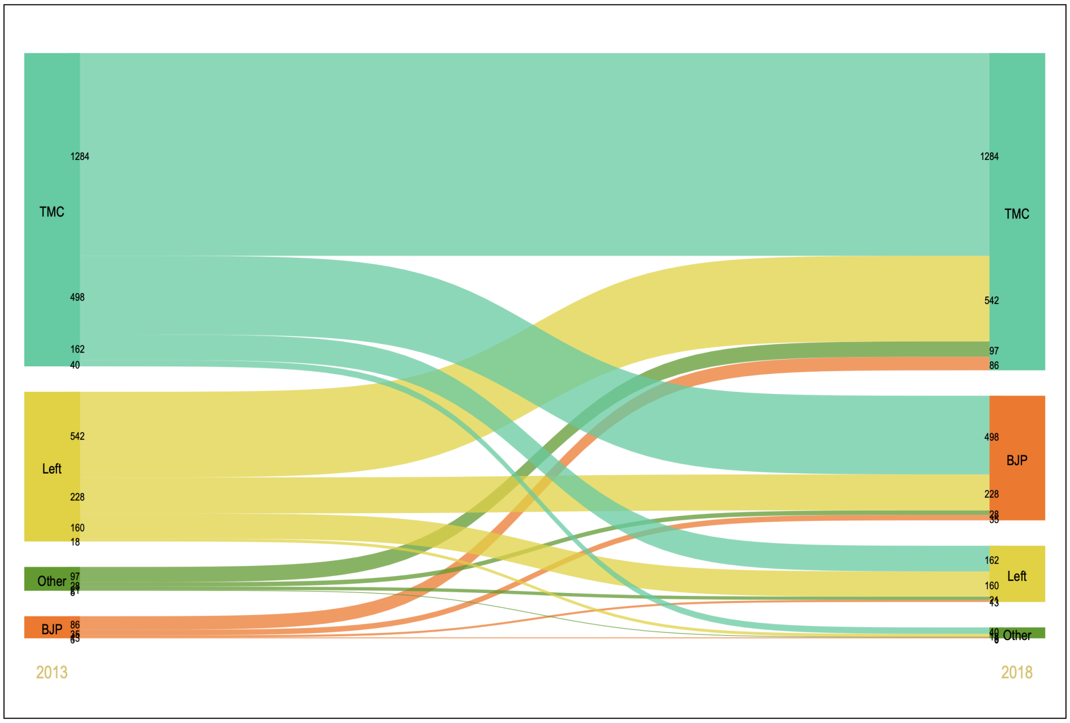
Notes: Proportion of Households voting for Left, BJP and TMC in straw poll conducted in 2013 and 2018 and 90% confidence interval presented.

in the actual elections. The smaller magnitudes are to be expected since the straw polls were conducted a few months before the actual elections, and voters' selection of the party to support may only have crystallised later. We also consider the possibility that some "shy" BJP supporters may have chosen not to participate in the straw poll.[21]

The longitudinal nature of our dataset allows us to look beyond the cross-sectional patterns and examine whether individual voters' political support remained consistent or changed between 2013 and 2018, and which party they changed their support to. As we see in the Sankey diagram in Figure 3, the increase in the BJP's vote share is simply the result of Left Front supporters switching to the BJP. It is true that a large number of households that voted for TMC in 2013 switched to the BJP in 2018, but at the same time, a larger number of 2013 Left Front voters switched to TMC in 2018. This indicates that rather than a simple swing of support from a left-wing to a right-wing political party, the

[21] A priori there is nothing to suggest that BJP supporters may have selectively refused to participate in the straw poll in 2018: 8.5% of those who cast a straw poll ballot for the BJP in 2013 did not participate in 2018, which is quite similar to the 8.2% refusal rate of households that marked the straw poll ballot for the TMC in 2013, and 6.9% refusal rate of those who cast a ballot for the Left Front in 2013. Neverthless, in Table A7 we present results from re-estimating our regressions after categorizing refusals in the straw poll in 2018 as votes for the BJP.

Figure 3: Vote Switching Patterns. Survey Data



Notes: Vote switching patterns of household heads between the two rounds presented.

changing voting patterns reflect a broader churning.

4 Underlying Voting Model and Regression Specification

We adapt a standard probabilistic voting model (Grossman and Helpman, 1996, Dixit and Londregan, 1996) where voters evaluate competing parties on a utilitarian dimension and a "residual" category that includes other considerations such as loyalty, identity, ideology, candidate image, party advertising and campaigns. The utilitarian dimension incorporates the voter's perception or expectation of how the parties' policies and programs will affect their material well-being. In our context, this is assumed to depend on the value that the household attaches to the welfare benefits they receive from the government.

Consider an election taking place in year t, where two parties $p = k, l$ compete. Voter i receives the benefit bundle $\mathbf{B}_{ipt}$ from party p at some point between election year t and the previous election year $t-1$, and this gives her material utility $\beta_p \mathbf{B}_{ipt}$, where β_p is the marginal utility vector of the benefit bundle from party p. To start with, we simplify by assuming that marginal utility does not vary with the voter's socio-economic status, so β_p is independent of i. Later we shall explore the robustness of our results when this assumption is relaxed.

The residual component varies with indicators of social identity such as religion, gender, caste or tribe, as well as idiosyncratic personal preferences. Voter i's ideological preference for party p is denoted by $\Gamma_{s(i)pt}\delta_{s(i)} + \epsilon_{ipt}$, where $s(i)$ denotes a vector of social identity characteristics of voter i, $\Gamma_{s(i)pt}$ is the common systematic component of the ideological preference of voter i with social identity s for party p at date t, δ_s is an indicator for group s, and ϵ_{ipt} is voter i's idiosyncratic ideological preference for party p, assumed to be identically and independently distributed across the population.

Let M_p denote the number of benefits that party p distributes, so $\mathbf{B}_{ipt} \equiv \{B_{imt}\}_{m=1,\ldots,M_p}$, $\beta_p \equiv \{\beta_{pm}\}_{m=1,\ldots,M_p}$. Then voter i who belongs to social group $s(i)$ votes for party k instead of $l \neq k$ if

$$\sum_{m=1}^{M_k} \beta_{km} B_{imt} + \Gamma_{s(i)kt}\delta_{s(i)} + \epsilon_{ikt} > \sum_{m'=1}^{M_l} \beta_{lm'} B_{im't} + \Gamma_{s(i)lt}\delta_{s(i)} + \epsilon_{ilt} \tag{1}$$

Denote $\gamma_{s(i),t} \equiv (\Gamma_{s(i)kt} - \Gamma_{s(i)lt})$, the relative ideological affinity of voters in social group $s(i)$ with party k compared with party l at date t. Then Condition (1) implies that i votes for party k in election year t if

$$[\sum_{m=1}^{M_k} \beta_m B_{imt} - \sum_{m'=1}^{M_l} \beta_{m'} B_{im't}] + \gamma_{s(i),t}\delta_{s(i)} > \epsilon_{ilt} - \epsilon_{ikt} \tag{2}$$

and the probability of this event is increasing in

$$[\sum_{m=1}^{M_k} \beta_m B_{imt} - \sum_{m'=1}^{M_l} \beta_{m'} B_{im't}] + \gamma_{s(i),t}\delta_{s(i)} \tag{3}$$

where the first expression represents the utility-based component and the second term the residual component.

Condition (3) leads us to the regression specification

$$\text{Vote Party}_{ipt} = \beta_0 + \beta_1 \text{State Benefits}_{it} + \beta_2 \text{Central Benefits}_{it} + \gamma_t \mathbf{X}_i + \varepsilon_{Ipt} \tag{4}$$

where binary variable Vote Party_{ipt} takes value 1 if household i votes for party p in election year t and 0 otherwise, and $\mathbf{X}_i$ is a vector of household socio-economic characteristics for household i. State Benefits_{it} and Central Benefits_{it} denote the total count of state and central benefits that household i received between years $t-1$ and t. For the 2013 round, central benefits are set equal to zero. The time-varying coefficient on household characteristics, γ_t, captures changes in the residual component, due to advertising, campaign mobilization efforts and intervening events that affect voters' sensitivity to identity issues.

The corresponding regression for the change in the likelihood that i votes for party p is given by

$$\Delta \text{Vote Party}_{ip} = \beta_1 \Delta \text{State Benefits}_i + \beta_2 \Delta \text{Central Benefits}_i + \Delta \gamma \mathbf{X}_i + \Delta \varepsilon_{Ipt} \qquad (5)$$

where Δ denotes the difference in the value of the variable between the two rounds. Thus, the likelihood that voter i switches allegiance from one party to another between 2013 and 2018 can be decomposed into that which is caused by a change in the flow of state and central benefits, and that which is caused by changing ideological or identity-based affinity with the party. In equation (5), the inclusion of household fixed effects controls for any time-invariant drivers of political support for a particular party.

An obvious concern with the specification in equation (4) is that the distribution of benefits may be endogenous to voting behavior. Higher level officials who control the allocation of benefit programs across different village councils could strategically target them to particular councils depending on the anticipated voting propensities of their residents in the next election.[22] If officials targeted benefits to "loyal" areas, this would positively bias our estimates of the effect of benefits on voting for the party; if officials targeted "swing" areas, the bias would depend on the effectiveness of the benefits at inducing voters to switch political support. In addition, the incumbent party's incentives to deliver benefits to different voters may depend on how competitive they perceive the next election to be. Less secure incumbents may deliver more benefits to swing areas, which could cause a negative bias.

To address these issues of endogeneity, we use a supply-side or "leave out" instrument for the scale of programs at the village council (GP) level. Specifically, the instrument is the product of two variables: the average number of benefits of either kind distributed in *other* GPs in the same district ($\bar{B}_{-v,dt}$), as in Levitt and Snyder Jr (1997), and fixed household characteristics (H_{ivd}), such as caste, landownership, education, and religion, which are significant determinants of whether a household receives benefits. So, the instrument for

[22] For example, Mahadevan and Shenoy (2023) show that in West Bengal the ruling party channels funds disproportionately to politically-aligned jurisdictions in water-stressed areas, which then delivers them more votes in the subsequent elections.

benefits received by household i in village v in district d in yeat t is given by:

$$B_{ivdt} = \bar{B}_{-v,dt} \times H_{ivd} \tag{6}$$

This instrument is used to predict the how GPs allocate benefits across individual households within each village. The fixed household characteristics are retained as controls in the regression, to allow for the fact that they could also directly affect voters' choice of political party. We also include district fixed effects in the regression, to control for unobserved heterogeneity across districts.

We assume that higher level officials representing the incumbent party at the district and block levels allocate the pre-determined budget for a particular benefit program across the different GPs in their jurisdiction, so as to maximize the likelihood that their own party is re-elected. However the exclusion restriction for the instrument is satisfied under the assumption that these officials take as given how GP leaders allocate the benefits across households within villages, and how households respond to these benefits with their votes. The model generates the following inter-village allocation for any given benefit program: in any given year, village v receives a budgetary assignment B_v

$$B_v = B + T_v - \sum_{v'} n_{v'} T_{v'} \tag{7}$$

where T_v is a parameter representing the "marginal political deservingness" of village v, n_v is the population weight of village v and B is the per capita budget for the district. The parameter T_v depends on which party controls the GP in village v, the voting propensities of its residents and the expected competitiveness of the next election. It is therefore likely to be correlated with village characteristics that affect how vote shares in the village respond to benefits, thereby creating a potential endogeneity bias when we regress votes on benefits received.

Equation (7) can be written as

$$B_v = B + (1 - n_v)T_v - \sum_{v' \neq v} n_{v'} T_{v'} \tag{8}$$

Observe that the cross-effect of $T_{v'}$ on B_v, when v differs from v', will be negligible if $n_{v'}$ is close to zero. Hence the third term in equation (8), which is proxied by the average allocation to all villages excluding v, is asymptotically independent of T_v if population weights go to zero (i.e., number of villages within the district becomes large). This is an instrument for B_v under the assumption that, conditional on district fixed effects, the

T_v's are independent across villages. The more deserving the other villages are, the less is available for any given village.[23]

The instrument has significant predictive power, as indicated by the large values of the first stage F-statistic for the first-stage regressions. Nevertheless, we evaluate the significance of the regression using a weak-instrument-robust Anderson-Rubin χ^2 test. Note that the negative coefficient on $\bar{B}_{-v,dt}$ in the first stage regression results presented in Table B1 is consistent with what we might expect to see when district or block officials must allocate a fixed budget across different GPs in their jurisdiction.

5 Estimating Effects of Benefits on Voting Patterns

5.1 Role of Welfare Benefits

To estimate the effect of state and central benefits on the voting patterns in our survey data, we run the regressions specified by equation (4), where the different state and central benefits are respectively aggregated to the two main regressors: the number of state benefits and central benefits received by the household. This implicitly assumes that households value all benefits equally. We later examine the robustness of the results to relaxing this assumption, and consider separately the effects of the two major state welfare schemes (NREGS and BPL cards) and two central schemes (in-house toilets and the LPG subsidy). The regressions are estimated separately for 2013 and 2018, to allow for the possibility that the effectiveness of state benefits at generating votes changed over time (see, for example Deshpande et al., 2019).

These regressions control for a range of household demographic and socio-economic characteristics: in particular, religion, caste, migration status, gender, marital status, education and occupation of the household head, household size and the district of residence. As we see in Panels A and B of Table 5, in both 2013 and 2018, the IV coefficients are larger in magnitude than the OLS coefficients. This suggests the OLS estimates are biased downwards, possibly reflecting insecure incumbents' relatively stronger motivation to pro-

[23] This approach has been adopted widely in recent work in developing country contexts: see for example Lamichhane and Mangyo (2011), Bai et al. (2019), Dang and La (2019), Sedai et al. (2020), Bardhan et al. (2021), Maitra et al. (2023a). The arguments of Levitt and Snyder Jr (1997) and Bardhan et al. (2021) imply that the recent criticism of this approach in settings with peer effects (Betz et al., 2018, McKenzie, 2021) does not apply to our setting where budgetary assignments are hierarchically determined by strategic considerations. Of course the standard disclaimer for IV estimates applies in the presence of heterogeneous treatment effects: therefore the IV estimate should be interpreted as a local average treatment effect on the sub-population that is "treated at the margin" due to variation in the instrument, in contrast to the OLS estimate which is a biased estimate of the average treatment effect applying to the entire population.

Table 5: Voting Patterns in 2018 and 2013. The Effect of Aggregate State and Central Benefits

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Voting for Party in 2018	TMC		BJP		Left	
Central Benefits 2014–2018	0.006	-0.031	0.027*	0.066	-0.005	-0.021
	(0.019)	(0.055)	(0.016)	(0.047)	(0.009)	(0.031)
State Benefits 2014–2018	0.060***	0.088***	-0.046***	-0.085***	-0.009*	-0.010
	(0.010)	(0.022)	(0.009)	(0.019)	(0.005)	(0.010)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.050	0.044	0.063	0.049	0.025	0.024
Average: No Central Benefits	0.552		0.235		0.097	
Average: No State Benefits	0.507		0.234		0.114	
First Stage F						
Central Benefits		74.52		74.52		74.52
		[0.00]		[0.00]		[0.00]
State Benefits		68.06		68.06		68.06
		[0.00]		[0.00]		[0.00]
Anderson-Rubin ($\chi^2(31)$)		92.22		102.82		40.64
		[0.00]		[0.00]		[0.09]
Panel B: Voting for Party in 2013	TMC		BJP		Left	
State Benefits 2010–2013	0.021**	0.061**	0.003	0.017*	-0.034***	-0.092***
	(0.010)	(0.026)	(0.003)	(0.010)	(0.010)	(0.025)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.371	0.365	0.062	0.058	0.278	0.264
Average: No State Benefits	0.526		0.055		0.374	
First Stage F						
State Benefits		151.34		151.34		151.34
		[0.00]		[0.00]		
Anderson-Rubin ($\chi^2(16)$)		87.72		116.62		143.35
		[0.00]		[0.00]		[0.00]

Notes: In Panel A the dependent variables are support for TMC (Columns 1 and 2), BJP (Columns 3 and 4) and Left Front (Columns 5 and 6) as elicited in the 2018 survey, and in Panel B they are as elicited in the 2013 survey. In columns 2, 4 and 6, the benefits variables are instrumented by the "leave out" instrument described in the text. Regressions also control for religion, caste, migration status, gender, marital status, education and occupation of the household head, household size and an indicator for residence in Hugli district. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. p-values in square brackets.

vide benefits and to target swing voters. The OLS estimate suggests that in 2018 a voter who received a state benefit was 6 percentage points more likely (relative to a household that did not receive any state benefits in the period 2014–2018) to vote for the TMC; the corresponding IV estimate is 8.8 percentage points. This increase came largely at the expense of the BJP (compare columns 2 and 4). The corresponding OLS and IV estimates suggest that receiving a central benefit increased the likelihood that a voter supported the BJP by 2.7 and 6.6 percentage points respectively (see columns 3 and 4), although the IV estimate is imprecise and is not statistically significant at the 10% level.

Did state benefits become less effective at generating votes for TMC between 2013 and 2018? Alternatively, did voters in 2018 credit the BJP (rather than the TMC) when they received state benefits? Our data suggest that the answer to both questions is no. The IV estimates presented in Panel B of Table 5 show that in 2013 each additional state benefit that an average household received increased the likelihood that they voted for TMC by 6.1 percentage points, decreased the likelihood that they voted for the Left Front by 9.2 percentage points and increased the likelihood that they voted for the BJP by 1.7 percentage points.[24] Rather than having a weaker effect, in 2018 the state benefits were even more effective at influencing how households voted.

The results in Table 5 provide estimates of the effect of state and central benefit receipt on voting propensities. Combining these with statistics on the receipt of benefits allows us to predict the effect of these benefits on vote shares. We show this calculation in Table 6. As we see in column 1, during 2010–13, the average household in our sample received 1.16 state benefits. When multiplied by the β coefficient of 0.061 (from Panel B in Table 5), this suggests that 7.1% of the vote share received by TMC in the 2014 election could be attributed to the state benefits delivered. Along the same lines, 2% of the vote share received by the BJP in the 2014 election could be attributed to state benefits. In column 2 we see that during 2014–2018 the average voter received 1.79 benefits. State benefits were now more effective at delivering votes for the TMC, and so this contributed 15.8% of their vote share. However unlike the previous period, the receipt of state benefits now *decreased* the likelihood that a household voted for the BJP, and therefore this decreased the BJP's vote share by 15.2 percentage points. Thus on net, the increased flow of state benefits, and their increased effectiveness at generating votes for the TMC, implies that state benefits increased the vote share of TMC by 8.7 percentage points from 2013 to 2018. When we also incorporate the effect of the new central benefits introduced after 2014, which contribute positively to the BJP's vote share but negatively to the TMC's vote share (column 3), the

[24]Recall that the Left Front rather than the BJP was the main competitor for the incumbent TMC in 2013.

Table 6: Predicted Effect of Aggregate State and Central Benefits on Votes

	State Benefits 2010–2013	State Benefits 2014–2018	Central Benefits 2014–2018	Estiimated/ Actual Effect
	(1)	(2)	(3)	(4)
Average Per Household (Q^t)	1.16	1.79	0.54	
Unit Effect on TMC Vote Share ($\hat{\beta}_{\text{TMC}}$)	0.061	0.088	-0.031	
Unit Effect on BJP Vote Share ($\hat{\beta}_{\text{BJP}}$)	0.017	-0.085	0.066	
Total Predicted Effect on TMC Vote Share ($\hat{\beta}_{\text{TMC}} \times Q^t$)	0.071	0.158	-0.017	
Total Predicted Effect on BJP Vote Share ($\hat{\beta}_{\text{BJP}} \times Q^t$)	0.020	-0.152	0.036	
Predicted Effect on Change in TMC Vote Share†				
State Benefits				0.087
Central Benefits				-0.017
Total Predicted Effect of Benefits (Central + State)				0.070
Actual Change in TMC Vote Share				-0.05
Predicted Effect on Change in BJP Vote Share‡				
State Benefits				-0.172
Central Benefits				0.036
Total Predicted Effect of Benefits (Central + State)				-0.136
Actual Change in BJP Vote Share				0.18

Notes: $t = 2013, 2018$; so Q^{2013} and Q^{2018} denote the average number of benefits received during the periods 2010–2013 and 2014–2018 respectively. Actual Change in TMC and BJP vote shares from the straw poll, reported in Figure 2. †: Predicted Effect on Change in TMC Vote Share given by $\hat{\beta}^{2018}_{TMC} \times Q^{2018} - \hat{\beta}^{2013}_{TMC} \times Q^{2013}$; ‡: Predicted Effect on Change in BJP Vote Share $\hat{\beta}^{2018}_{BJP} \times Q^{2018} - \hat{\beta}^{2013}_{BJP} \times Q^{2013}$. By construction, there were no central benefits before 2014.

total effect of is a slightly smaller 7 percentage points increase in the TMC's share (column 4).

This indicates that the delivery of state benefits by the TMC-led state government contributed positively to their vote share, contrary to the 5% decline actually observed in the 2018 poll. Conversely, the new central benefits are estimated to have contributed a 3.6 percentage point increase in the BJP's vote share (column 3). When we add to this the negative effect of state benefits on the BJP's vote share, the net effect is a 13.6 percentage point decline in the predicted BJP vote share (in contrast to the 18% actual increase). Clearly, the changes in benefit flows fail to account for observed changes of vote shares of either party.

5.2 Extensions and Robustness Checks

Table 7: Switch in Voting Patterns

	Against TMC		To TMC		To BJP		Against Left	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Difference in Central Benefits	-0.018	0.007	0.004	-0.001	0.014	0.050	0.009	0.021
	(0.014)	(0.039)	(0.010)	(0.034)	(0.015)	(0.047)	(0.007)	(0.025)
Difference in State Benefits	-0.018***	-0.043***	0.015***	0.014*	-0.027***	-0.060***	-0.001	-0.007
	(0.007)	(0.014)	(0.004)	(0.008)	(0.007)	(0.015)	(0.003)	(0.006)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.227	0.218	0.430	0.430	0.065	0.049	0.796	0.795
First State F								
Difference in Central Benefits		71.41		71.41		71.41		71.41
		[0.000]		[0.000]		[0.000]		[0.000]
Difference in State Benefits		130.08		130.08		130.08		130.08
		[0.000]		[0.000]		[0.000]		[0.000]
Anderson Rubin ($\chi^2(30)$)		64.94		244.24		93.34		156.43
		[0.000]		[0.000]		[0.000]		[0.000]

Notes: The dependent variables indicate a switch in political support toward and against a particular party from 2013 to 2018. In columns 2, 4, 6 and 8, the benefits variables are instrumented by the "leave out" instrument described in the text. Regressions also control for religion, caste and the migration status of household, gender, marital status, education and occupation of the household head, household size, indicator for residence in Hugli district and party voted for in 2013. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

5.2.1 Switch in Voting

We may also be concerned that the village council may selectively allocate welfare benefits to household groups that were more likely to respond by voting for the political party that controls the council. We address this concern by examining the robustness of the results to using the specification in equation (5). This allows us to examine how voters' allegiance switches were affected by changes in their receipt of benefits. In Table 7, we present results from regressions for the probability that voters switched their support against TMC (Columns 1–2), and for the probability that they switched to TMC (Columns 3–4). This is followed by regressions for the likelihood that they switched their support to the BJP (Columns 5–6), and away from the Left Front (Columns 7–8).[25] We present both the OLS and the IV estimates, where the instrument for changes in state benefits is the change in the leave out instrument for per capita benefits in a given GP, interacted with the same household characteristics. As the first stage F-statistics show, the instruments are strong predictors of the change in benefit flows.

[25] Since in the 2013 data very few voters supported BJP, and between 2013 and 2018 very few voters switched support to the Left Front, we do not run the corresponding regressions for those phenomena.

The IV results show that an additional state benefit received reduced the likelihood that a household switched their political support away from TMC by 4.3 percentage points (column 2) and reduced the likelihood that they switched support to the BJP (by 6 percentage points, column 7). Receipt of an additional state benefit also increased the likelihood of switching to TMC, but this effect is small (1.4 percentage points). On the other hand, an increased central benefit had no effect on switching to or away from TMC. It induced a 5 percentage point increase in the likelihood of switching to the BJP, but the IV estimate is not statistically significant (column 6). Hence our preceding results are robust: clientelistic state benefits continued to help local incumbents in 2018, and the effects of central benefits in helping the BJP are statistically not significant.

5.2.2 The Role of Changes in Household Economic Circumstances

A large and growing literature seeks to understand the global increase in voters' support for populist and right-wing nationalist parties. Many scholars have argued that is caused by the increase in economic insecurity and distress from globalization, trade shocks or immigration (see, for example, Colantone and Stanig, 2018, 2019, Autor et al., 2020, Oliveira, 2022). Moreover, benefit allocations may have been affected by income shocks experienced by households. We now examine whether changes in household economic circumstances may have affected voting patterns, and whether our preceding results continue to hold after controlling for such shocks.

Using data on farm incomes (specifically from the cultivation of potatoes) and non-farm incomes collected through our household surveys, we create an indicator for whether the household faced a decrease in employment income, and whether their returns from potato cultivation declined between 2010–13 and 2018.[26] We use the voting regression specification for 2018 from Table 5, and in addition to including benefits received and other controls, we augment it to include these measures of income decline.

Table 8 shows the corresponding results for the likelihood that a sample household supported the TMC and BJP respectively. We see that the coefficients on state and central benefits are unaffected even after we control for the possibility that our previous findings were driven by households that faced worsening economic circumstances. Moreover, the estimated coefficients on the measure of economic decline are quantitatively and statistically

[26] Potatoes are the principal cash crop cultivated in this region. Returns from potato cultivation are measured in terms of value added, which is the difference between revenue from potato sales and the costs of purchased inputs. Both sources of income are adjusted by a cost of living index. Recall from Table 1 that real employment income fell during the period for 68.75% of households while real potato value-added fell for 8.5% of households.

Table 8: Post-2013 Economic Circumstances and Voting in 2018

	Vote TMC		Vote BJP	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Decline in Potato Value-added	0.000	0.006	-0.004	-0.012
	(0.032)	(0.032)	(0.026)	(0.027)
Decline in Employment Income	-0.004	-0.001	0.000	-0.003
	(0.023)	(0.024)	(0.020)	(0.021)
Central Benefits 2014–2018	0.006	-0.032	0.027*	0.066
	(0.019)	(0.055)	(0.016)	(0.047)
State Benefits 2014–2018	0.060***	0.089***	-0.046***	-0.085***
	(0.010)	(0.022)	(0.009)	(0.019)
Constant	0.428***	0.388***	0.383***	0.437***
	(0.072)	(0.079)	(0.063)	(0.072)
Number of Observations	3,500	3,500	3,500	3,500
R-squared	0.050	0.044	0.063	0.048

Notes: Regressions also control for characteristics of the household head (gender, education, age, occupation), household size, landholding, identity of household (gender of head, caste, religion, migrant status) and Hugli resident. In columns 2 and 3, IV regression results are presented. The benefits variables are instrumented by the "leave out" instrument described in the text. Employment income and Potato Value added in real terms (using the All India Price Index Number for Agricultural Labourer, General Index, $1986-87 = 100$). Employment Income and Potato value added in Rs. ('0000). Change in employment income = Employment income (2018) – Employment income (2010–2013). Change in potato value-added = Potato value-added (2018) – Potato value-added (2010–2013). Decline in Employment income = Change in Employment income < 0. Decline in Potato value-added = Change in Potato value-added < 0. Standard errors, clustered at the village level in parentheses. Significance: $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$.

insignificant. Thus there is no evidence that changes in economic circumstances directly affected voting patterns in 2018.[27]

5.2.3 Other Robustness Checks

The Appendix includes a number of additional robustness checks to alternative specification in Table 5. We briefly summarize the results here and present more details in Sections A1.1

[27]In Table A5 in the Appendix we investigate possible interaction effects between economic decline and receipt of state or central benefits. Contrary to the hypothesis that declines in household income cause households to vote for right-wing nationalist parties, we find that households that experience a decline in employment income *and* receive state benefits are 10 percentage point more likely to vote for the TMC, and also less likely to vote for the BJP in 2018.

— A1.4 in the Appendix.

Interactions of Voting patterns with the Local Incumbent: Table A6 finds evidence consistent with the idea that when a household whose village council is controlled by the TMC receives a state benefit, it may attribute this to the TMC rather than some other party, and therefore become especially more likely to vote for the TMC in the subsequent election. However the the main results are unaffected.

Shy BJP Voters?: While no household head refused to participate in the 2013 poll, 8% refused in the 2018 poll. If households that received benefits became more likely to vote for the BJP but also refused to participate in 2018 straw poll then our previous results are biased. To address this concern, we rerun the regressions after recoding these households non-votes as votes for the BJP. As we see in Table A7, the results are very similar.

Allowing Individual Welfare Benefits to Have Different Effects: Households may place different value on the different state / central benefits, and correspondingly, receiving these benefits may generate different effects on their votes. If so, aggregating them may mute the effects of the most effective vote-getting benefit schemes. Table A8 presents results from regressions estimated separately for the two most important state and central benefit programs: NREGS and BPL cards, and in-house toilets and LPG subsidies. While receiving the NREGS workfare strongly increases the likelihood that a household votes for the TMC, the effects of BPL cards and of the two central programs are smaller and statistically insignificant. We also know that the NREGS program shrank after 2014, suggesting that in disaggregated results state benefits may have a smaller effect on the change in TMC vote share. To check this, Table A9 computes the implied effect on predicted vote shares. While changes in NREGS benefits have no effect on the TMC vote share they still predict a 11.4% decline in BJP vote share. Overall, the two most important state benefits together deliver a 10% *decrease* in the BJP vote share. Thus we continue to find that changes in flows of the four major benefit schemes cannot explain the substantial increase in the BJP's vote share over the period 2014 to 2019.

Heterogeneous Voting Impacts across Different Land Categories: Our base regression specification estimated average voting responses across different household groups. However, the literature on clientelism has found that poorer groups are more likely to respond favourably to the receipt of benefits, as one might expect if such groups have a higher marginal utility of benefits (Stokes, 2005, Bardhan et al., 2021). Table A10 shows OLS estimates of voting regressions run separately for the four land categories. Irrespective of the landholding category, an increase in central benefits is not associated with a change in the likelihood of voting for either party. The effects of state benefits on the likelihood that a household votes for the TMC or BJP do not vary much across different land groups. The implied effects for predicted changes in vote shares are shown in Table A11: they predict a 7.2 percentage point increase in the TMC's vote share and a 6.9 percentage point decrease in the BJP's vote share.[28]

5.3 Alternative Explanations

In this Section we discuss potential alternative explanations for the post-2014 increase in BJP vote shares.

5.3.1 2018 Panchayat Election Violence

During the 2018 panchayat (local government) elections in West Bengal, the media reported a number of violent incidents around the state. Observers suggested that the violence was initiated or perpetrated by supporters of the TMC in order to intimidate their political opponents into withdrawing their candidacy. This violance may have turned voters against the TMC in the 2019 Parliamentary elections, and thereby contributed to the increase in the BJP's vote share. We check this in Figure A6 in the Appendix by examining how the BJP's vote share varied across constituencies depending on the proportion of the 2018 panchayat elections where the TMC candidate ran unopposed.[29] There is no correlation between the incidence of unopposed TMC candidature and voting patterns in the 2019 election.

5.3.2 The Residual Component: Variation Across Socio-Economic Groups

Finally, we explore variations in the vote shares of different socio-economic groups, which may be the result of factors in the residual category in our model: ideology and identity considerations.

[28]We repeat the exercise by examining the heterogeneous voting impacts across the different income quantiles. The estimated effects for the different income quantiles are presented in Table A12. In Table A13 we present the corresponding implications of these estimates for the predicted vote shares of TMC and BJP. Once again, we see that our key results are robust to allowing the targeting patterns to vary across different income quantiles.

[29]The analysis in Section 5.3.1 uses data made available by the West Bengal state election commission for the entire state. TMC candidates ran unopposed in approximately 33% of seats, which we take as a measure of the political violence and intimidation by TMC party activists.

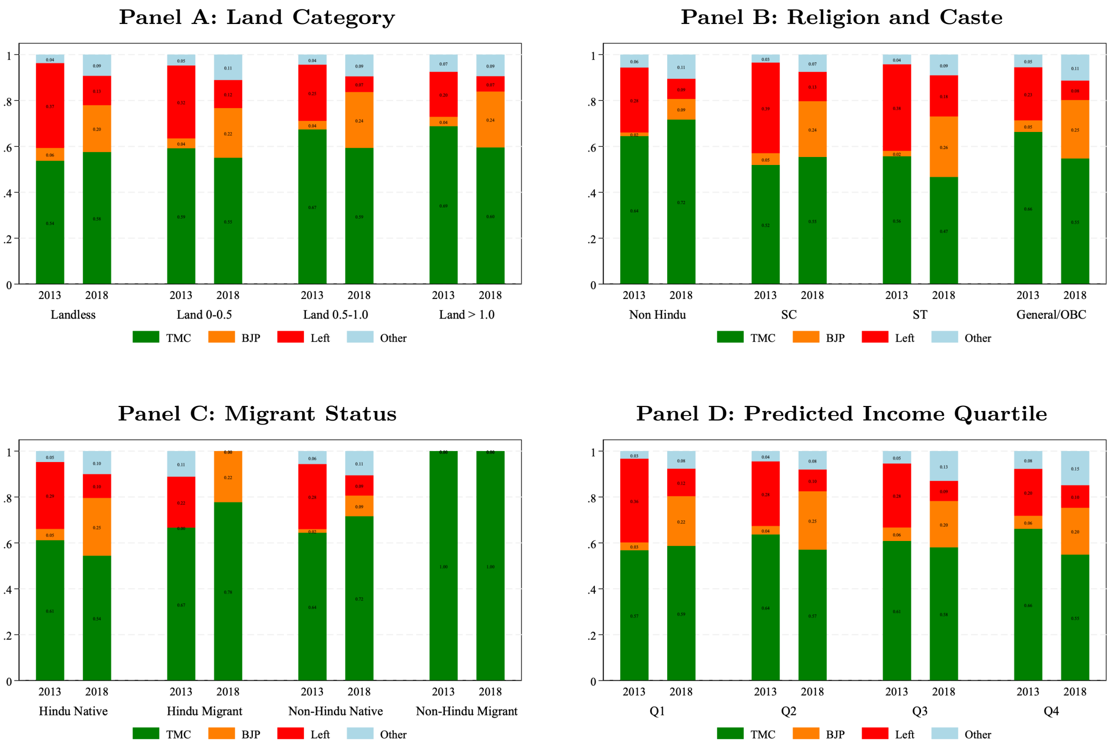
Figure 4 shows how vote shares changed over time in different population sub-groups. Panel A shows that the increase in the BJP vote share was nearly uniform across different landowning categories, rising from 4–6% in 2013 to between 20–24% in 2018. A similar pattern emerges across different income quartiles in Panel D. Panel B shows the shift was markedly smaller among non-Hindus (an increase of 9%), compared to an increase of 25% among general caste and OBCs, 24% among SCs and 26% among STs. Panel C compares shifts across groups defined by religion and migration status of the household. Among Hindus, the BJP vote share increased by 20–24% both among migrants and non-migrants. However among non-Hindus, the BJP's vote share increased by far less among recent migrants than among non-migrants. All Non-Hindu migrants voted for the TMC in both years. Hence non-Hindus and in particular, recent non-Hindu migrants were much less likely to switch support to the BJP. Strikingly, this is despite the fact that they were less likely to receive state benefits than Hindu households (See Table A15). This suggests that other factors may have prevented them from switching support to the BJP, in line with the growing importance of voting based on religion and immigration.

Therefore, in Table 9, we verify that the patterns are robust to controlling for the number of benefits received. The coefficients on the indicator variables for household socio-economic categories show that in 2018, compared to Hindu non-migrant households, non-Hindu households were 20 percentage points more likely to vote for the TMC, and 17 percentage points less likely to vote for the BJP. These effects strengthened between 2013 and 2018.[30] Conversely, even though they received more state benefits, SC and ST households were less likely to vote for the TMC in 2018 than general caste / OBC households were; the effect is statistically significant for ST households. Hence we see asymmetries of voting patterns across religion and caste lines after controlling for benefits received and a large range of other demographic characteristics, which suggests that non-economic factors such as religious and ethnic identity were important.

Finally, we consider a welfare benefit-driven explanation for why Hindus and SCs/STs were more likely to switch their votes to the BJP compared to non-Hindus. Not only may voters favor the political party whom they credit for the benefits they receive, they may also oppose political parties that they believe act unfairly. For example, non-recipients

[30]Different socio-economic groups may also have differing vote responses to receiving welfare benefits. Table A14 in the Appendix examines interactions between benefits and household characteristics. It shows that non-Hindus were less responsive to the receipt of state benefits in 2018 and non-responsive to central benefits. Even though they did not receive any benefits in 2018, non-Hindus were significantly more likely to vote for the TMC (23.6%) and significantly less likely to vote for BJP (18%); the corresponding effects in 2013 were much smaller. In other words, non-Hindus appear to have been a secure "vote-bank" for the TMC.

Figure 4: Vote shares by Household Characteristics. Survey Data



Notes: Percentage of Households voting for Left, BJP and TMC in straw poll conducted in 2013 and 2018 by household characteristics presented. Percentage of households that belong to each land category: 20, 40, 23, 18 (Panel A). Percentage of households that belong to each religion and caste category: 15, 69, 6, 10 (Panel B) Percent of households that belong to each migrant category: 80; 5; 15; 1 (Panel C). Predicted Income Quantiles (Panel D) computed using the predicted value of income from regression results presented in Table A2.

of a benefit who believed they were deserving may resent the political party more if they perceive that other undeserving households received the benefit. In this hypothesis, Hindu native households may resent the TMC if they believe it was "appeasing" minorities such as Muslims and migrants in order to obtain their votes.

However, as we show in Table A15 in the Appendix, even after controlling for landownership, there was no differential in the likelihood that non-Hindus and Hindus received either state or central benefits. If anything, Non-Hindu recent migrants were significantly less likely to receive both state and central benefits. Thus we fail to find any evidence that the TMC disproportionately delivered benefits to non-Hindus or non-Hindu migrants, as claimed by the "appeasement" hypothesis.[31]

[31] Our data do not allow us to test directly whether Hindu voters perceived that Muslims were being appeased. However, if voters believed that Muslims were disproportionately likely to receive benefits, then

Table 9: **Regression of Voting Patterns on Household Characteristics**

	Vote for Party in 2018			Vote for Party in 2013		
	TMC	BJP	Left	TMC	BJP	Left
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Hindu Household	0.198***	-0.167***	-0.016	-0.001	-0.044***	0.044*
	(0.035)	(0.030)	(0.020)	(0.025)	(0.013)	(0.024)
Recent Migrant Household	0.220	-0.057	-0.089***	0.055	-0.020	-0.139
	(0.161)	(0.157)	(0.027)	(0.100)	(0.021)	(0.086)
Non-Hindu × Recent Migrant	0.125	-0.130	0.021	0.424***	0.036	-0.335***
	(0.154)	(0.152)	(0.035)	(0.104)	(0.025)	(0.096)
SC Household	-0.032	0.029	0.030	-0.078***	-0.011	0.106***
	(0.029)	(0.027)	(0.019)	(0.024)	(0.010)	(0.025)
ST Household	-0.122*	0.032	0.090*	0.009	-0.039***	0.039
	(0.064)	(0.052)	(0.052)	(0.047)	(0.014)	(0.049)
Landless	-0.082**	0.028	0.054**	-0.026	0.002	0.066**
	(0.039)	(0.033)	(0.022)	(0.030)	(0.015)	(0.029)
Landholding 0—0.5 acres	-0.094***	0.004	0.058***	-0.040*	0.001	0.061**
	(0.031)	(0.028)	(0.017)	(0.024)	(0.013)	(0.023)
Landholding 0.5—1 acres	-0.016	0.006	0.003	0.010	-0.005	0.026
	(0.030)	(0.026)	(0.015)	(0.022)	(0.011)	(0.021)
Constant	0.426***	0.383***	0.075**	0.526***	0.049*	0.396***
	(0.068)	(0.061)	(0.034)	(0.057)	(0.025)	(0.054)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.050	0.063	0.025	0.371	0.062	0.278

Notes: OLS regression results presented. Regressions also control for characteristics of the household head (gender, education, age, occupation), household size, landholding, state benefits received (2014–2018 or 2010–2013), central benefits received (2014–2018) and Hugli resident. Recent immigrant denotes households where the head was not born in the village but migrated less than 10 years previously. Standard errors, clustered at the village level in parentheses. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

6 Concluding Comments

To summarize, we find no evidence that compared to the state benefit schemes, new central benefit schemes were better targeted to poorer or SC/ST households, or that the targeting of state programs improved after 2014. There is little evidence that state benefits became less effective at generating votes for the TMC after 2014. In line with these findings, the sharp increase in the vote share of the BJP in the 2019 parliamentary elections in the districts we study cannot be explained by such changes, or by changes in household incomes. Instead, we find that the increased support for the BJP comes disproportionately from certain religious and caste groups, even after controlling for the receipt of welfare benefits. This suggests that ideological and social identity considerations have played a

our results suggest this belief was not grounded in fact. The misperception may be driven by a confluence of ideology and political advertising.

more important role in the rise of the BJP in West Bengal than economic issues and the distribution of welfare benefits have.

Our results agree with the specific findings of Deshpande et al. (2019) at the all-India level in that the reach of NREGS benefits has decreased, and they have become less effective at generating votes for regional incumbents, and that the new central benefits introduced after 2014 helped increase BJP's vote share. However our overall conclusion differs markedly from theirs, because we additionally incorporate other state benefits programs, whose scale increased after 2014 and which became more effective at generating votes for the TMC. Moreover, the quantitative effect of central benefits on the BJP vote share was marginal and typically statistically insignificant. Consequently assessing the combined impact of the changes in different state and central programs, we predicted that the TMC vote share would have increased by 7% between 2013 and 2013, while the BJP's vote share would have declined by 13%, contrary to the actual patterns observed.

Our findings are also consistent with a number of other recent articles on West Bengal politics that draw attention to the Trinamool Congress's political strategies. Dey and Sen (2020), Shenoy and Zimmerman (2020), Mahadevan and Shenoy (2023) provide detailed empirical evidence of political clientelism in West Bengal during the post-2011 period after the TMC acquired majority control of state and local governments. Bhattacharya and Dasgupta (2023) suggest that the structural characteristics of the rural labour market and the low labour force participation rate of women in West Bengal ensure that the electorate remains dependent on transfers from the state government to stabilize household incomes in an environment of fluctuating and uncertain earnings. Nath (2022) provides data and ethnographic evidence that since 2011, the TMC has increasingly encouraged religious and cultural celebrations and the use of traditional community-based mechanisms of dispute settlement, which has encouraged minorities to vote for the TMC.

Data limitations prevented us from examining other possible sources of anti-TMC-incumbency, such as citizens blaming the TMC's leaders and party workers for corruption, or governance failures on other dimensions such as security or dispute settlement. We are also unable to include other districts or states in the analysis. The collection and use of more data from other parts of India can allow researchers to ascertain to what extent our results extend to other locations and dimensions of governance.

Readers may be concerned that our findings are specific to West Bengal and do not apply to other Indian states. However, we believe the experience of West Bengal is important for its own sake; its population of 90 million makes it comparable in size to countries like the UK or France. Moreover, it would be premature to declare that our results would not extend to other Indian states. For instance, our findings for West Bengal echo Deshpande et al. (2019)'s main findings at the all-India level: the NREGS program became less important at generating votes for the regional incumbent, and new central benefits introduced after 2014 contributed to the increase in the BJP's vote share. However, our data allow us to go a few steps beyond this to examine the scale and effectiveness of all other state benefit programs that expanded or were introduced after 2014, and thus to paint a more complete picture of the extent to which such state benefits may have changed how citizens voted. Once suitable data for such a comprehensive analysis become available at the all-India level, it will be possible to examine whether or not a similar phenomenon occurred at the all-India level. This remains an important research objective for the future.

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Online Appendix

A1 Additional Robustness Checks

A1.1 Interactions of Voting patterns with Local Incumbency

In Table A6 we add an interaction between benefits received (state and central in the period 2014–2018 and state benefits in 2010–2013) with an indicator for the party that had the most seats in the GP. The estimates indicate that in 2018, an additional state benefit received in a GP controlled by TMC was associated with a statistically significant 6.1 percentage point increase in the likelihood that the household voted for TMC, and a 4.85 percentage point decline in the likelihood that they voted for BJP. In contrast, in a GP not controlled by TMC, the state benefit had a weaker effect on influencing how households voted: an additional state benefit only increased the vote share of TMC by 3.2 percentage points, and decreased the vote share of BJP by 2.4 percentage points; the effect is statistically significant only for the decrease in the BJP's vote share. We see similar patterns in 2013: in a GP controlled by the Left Front, state benefits were significantly less likely to translate into votes for TMC; whereas in GPs not controlled by the Left Front, an additional state benefit increased TMC's vote share by 11.4 percentage points, decreased the BJP's vote share by 2.9 percentage points, and decreased the Left Front's vote share by 10.4 percentage points.

A1.2 Shy BJP Voters?

Recall that while no household refused to participate in the straw poll in 2013, 8.1% of households chose not to participate in the voluntary straw poll in 2018. Do the main results change if we categorize these refusals as shy BJP voters? We re-estimate the regression corresponding to equation (4) and in Table A7 we present the corresponding estimates. Qualitatively the results are similar to those presented in columns 3 and 4 of Table 5: the IV estimates presented in column 2 imply that an additional state benefit received in the period 2014–2018 reduces the likelihood that the household votes for BJP by 7.6 percentage points. An additional central benefit received during the same period increases the likelihood that the household votes for BJP by 4.2 percentage points which was statistically insignificant.

A1.3 Allowing Individual Welfare Benefits to Have Different Effects

In Table A8 we present results of regressions estimated separately for the two most important state and central benefit programs: NREGS and BPL cards, and in-house toilets and LPG subsidies. The IV estimates use "leave out" instruments constructed separately for each benefit program. The first stage regressions have large F-statistics for each program and survey year. As we see in the table, the coefficients vary considerably across programs: the receipt of NREGS workfare has a much larger effect on votes than BPL cards, and is the only state benefit with a statistically significant IV effect in 2018 (coefficient = 0.224, p-value < 0.01). Neither of the two central benefits have a statistically significant effect (and surprisingly receipt of LPG subsidy has a negative point estimate in column 4, but the effect is not statistically significant). The NREGS was more effective at boosting TMC's vote share in 2013 (coefficient = 0.120, p-value < 0.01), but it also had a large point estimate of a negative impact on the BJP's vote share in 2018 (coefficient = -0.201 , p-value < 0.01). Interestingly, Deshpande et al. (2019) argue that at the All India level, in 2019 voters credited BJP when they received the NREGS benefit even though the program was introduced by the previous UPA government. However, in the context of West Bengal, we find that receiving the NREGS workfare in fact reduced the likelihood that a household voted for the BJP. In fact our data suggest that receiving the NREGS benefit had a positive effect on votes for TMC.[32]

In Table A9 we compute the implied effect on predicted vote shares. While NREGS employment has no effect on TMC vote share it is associated with a 11.4% decline in BJP vote share. Overall, the two most important state benefits aggregate to a 10% decrease in BJP vote share. Again, we continue to find that benefits alone cannot explain the substantial increase in the BJP's vote share over the period 2014 to 2019.

A1.4 Heterogeneous Voting Impacts across Different Land Categories

The preceding analysis has examined the effect of benefit programs on the average voter. In fact, however, households of different economic status may respond differently. To address this concern, Table A10 shows OLS estimates of the voting impacts of state and

[32] We have categorized NREGS as a state benefit, but the results do not depend on this categorization.

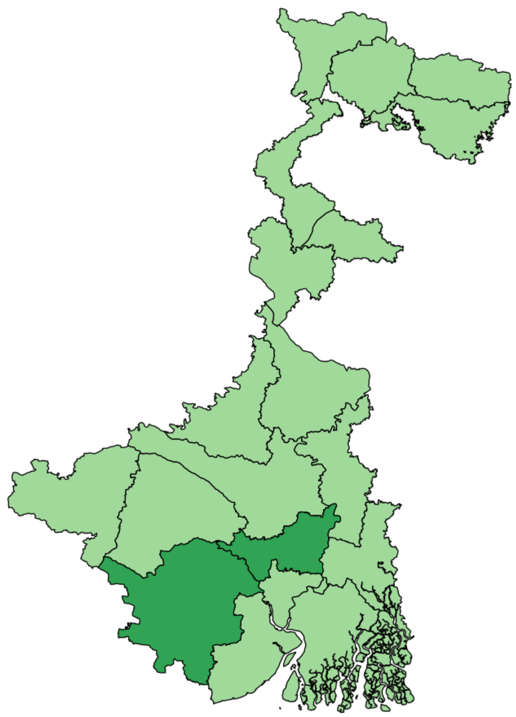
central benefits, from regressions run separately for the four land categories (landless, Landholding 0–0.5 acres, Landholding 0.5–1.0 acres and Landholding $>$ 1.0 acres), using the same specification as in equation (4). Irrespective of the landholding category, an increase in central benefits is not associated with a change in the likelihood of voting for either party. On the other hand, an increase in the number of state benefits received increases the likelihood of voting for TMC and reduces the likelihood of voting for BJP. The effects are quite uniform across land categories: from a 6.7 percentage point increase in the likelihood of voting for TMC for households in the 0–0.5 acre category to 4.5 percentage points for households with more than 1 acre; and from 5.3 percentage point fall in the likelihood of voting for BJP for the landless to a statistically not significant 3.4 percentage point fall for households with more than 1. acre. In general the effects are stronger than in 2013.

In Table A11 we present the implications of these effects for the predicted vote shares of TMC and BJP. The results predict an increase in TMC's vote share by 7.2 percentage points an a decrease in BJP's vote share by 6.9 percentage points. The central benefits themselves though predict a 1.4 percentage point increase in BJP's vote share, which is only 7.8% of the true increase in the vote share of BJP. Therefore, our earlier results are robust to allowing targeting patterns to vary across different land categories.

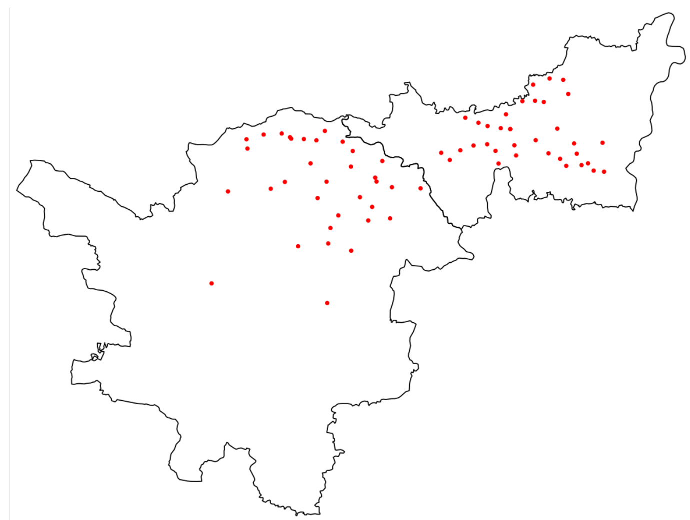
Finally Table A12 presents the corresponding OLS estimates of the voting impacts of state and central benefits, from regressions run separately for the four different income quartiles. For voters in the second income quartile, an increase in central benefits is associated with an increased likelihood that they vote for the BJP. Somewhat surprisingly, we also see an increased tendency for voters in the fourth income quartile to vote for the TMC. Households in the first, second and fourth quartiles responded to state benefits in 2018 by roughly the same extent, while the third quartile shows a smaller and insignificant effect. Hence we find weak evidence that poorer households voters were more responsive to state benefits. Note also that voters in all groups were markedly more responsive to state benefits in 2018 than in 2013. In Table A13 we see the corresponding implication of these estimates for the predicted vote shares of the two parties. The results predict an increase in the TMC's vote share by 7.2 percentage points, and a decrease in the BJP's vote share by 5.7 percentage points. The central benefits alone predict a rise in the BJP vote share of 1.5 percentage points, which is only 8.3% of the observed true increase in the vote share of the BJP.

Figure A1: Survey Districts and Sample Villages

Panel A: Survey Districts



Panel B: Location of GPs in Sample



Notes: Our sample villages are from Hugli and Pashchim Medinipur, the districts in darker shade (in Panel A). In Panel B the red dots denote the location of our sample villages.

Table A1: Household Characteristics by Land category and Social Group

	(1)	(2)	(3)	(4)
Panel A:	Landless	Landholding 0–0.5 acres	Landholding 0.5–1.0 acres	Landholding > 1.0 acres
Head: Less than Primary Schooling	0.794	0.695	0.454	0.347
	(0.404)	(0.460)	(0.498)	(0.477)
Head occupation: Cultivation	0.129	0.405	0.741	0.735
	(0.336)	(0.491)	(0.438)	(0.441)
Kuchha House	0.623	0.624	0.535	0.437
	(0.485)	(0.485)	(0.499)	(0.496)
Average Income 2010–2013 (Rs.)	39747.570	45356.140	49048.380	84328.390
	(34415.980)	(47086.490)	(53271.880)	(114097.300)
Number of Households	681	1399	804	616
Panel B:	ST	SC	Non Hindu	Others
Head: Less than Primary Schooling	0.796	0.780	0.726	0.450
	(0.404)	(0.415)	(0.446)	(0.498)
Head occupation: Cultivation	0.263	0.315	0.506	0.587
	(0.442)	(0.465)	(0.500)	(0.492)
Kuchha House	0.814	0.701	0.538	0.493
	(0.390)	(0.458)	(0.499)	(0.500)
Average Income 2010–2013 (Rs.)	51320.020	47284.060	46514.760	56020.040
	(85950.810)	(52657.420)	(55811.000)	(71402.450)
Landless	0.311	0.318	0.236	0.110
	(0.464)	(0.466)	(0.425)	(0.313)
Landholding 0–0.5 acres	0.371	0.490	0.378	0.364
	(0.485)	(0.500)	(0.485)	(0.481)
Landholding 0.1–1.0 acres	0.222	0.131	0.207	0.287
	(0.417)	(0.338)	(0.406)	(0.452)
Landholding > 1.0 acres	0.096	0.061	0.179	0.240
	(0.295)	(0.239)	(0.384)	(0.427)
Number of Households	167	922	569	1841

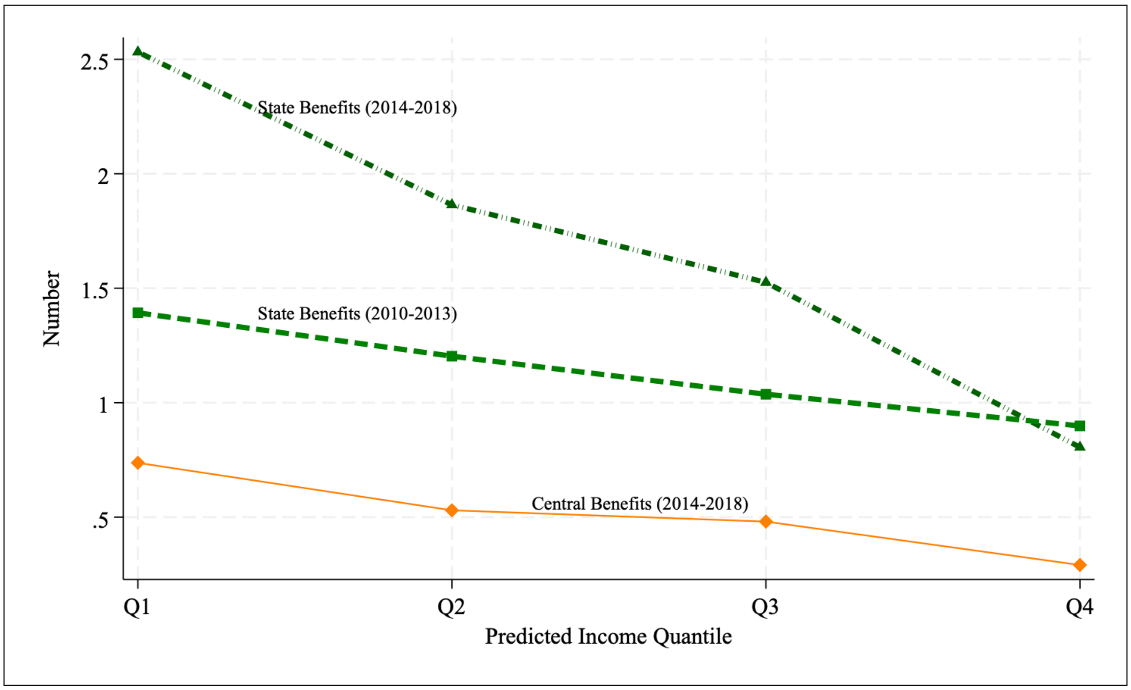
Notes: Panel A presents the averages by land category. Panel B presents the averages by Household Identity (Caste and Religion).

Table A2: Correlates of Household Income

	OLS (1)	VFE (2)
Landless Household	-10,899.628***	-9,336.408***
	(2,205.680)	(2,833.307)
Household Head less than Primary School	-7,774.164***	-6,345.389**
	(2,633.482)	(2,603.427)
Female headed Household	-1,519.588	-4,426.268
	(6,891.805)	(7,078.230)
Occupation of Household Head: Labour	-3,821.722**	-6,430.689***
	(1,780.898)	(1,980.779)
Kuchha House	-11,031.288***	-14,113.853***
	(2,627.868)	(2,754.462)
Constant	66,284.370***	67,833.730***
	(3,103.520)	(2,342.418)
Number of Observations	3,500	3,500
R-squared	0.022	0.054

Notes: Dependent variable: Average total household income during the period 2010–2013. Regression in column 2 includes village fixed effects. Standard errors, clustered at the village level in parentheses. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Figure A2: Number of Central and State Benefits Received by Predicted Income Quantiles



Notes: Predicted Income Quantiles computed using the predicted value of income from regression results presented in Table A2.

Table A3: Targeting. Cumulative Proportion of Benefits accruing to Households in different Land categories

Land Category	Central Benefits 2014–2018				State Benefits 2014–2018	
	In-House Toilet	LPG Subsidy	Jan Dhan	Farmer Credit Card	NREGS Employment	BPL Card
	(1)	(2)	(3)	(4)	(5)	(6)
Landless	0.214	0.327	0.262	0.000	0.264	0.316
Landholding upto 0.5 acres	0.723	0.810	0.660	0.410	0.710	0.795
Landholding upto 1.0 acres	0.909	0.956	0.871	0.709	0.904	0.944

Notes: Proportion accruing to households owning below the specified cultivable landholding size presented. Omitted category: households with landholding $>$ 1.0 acres.

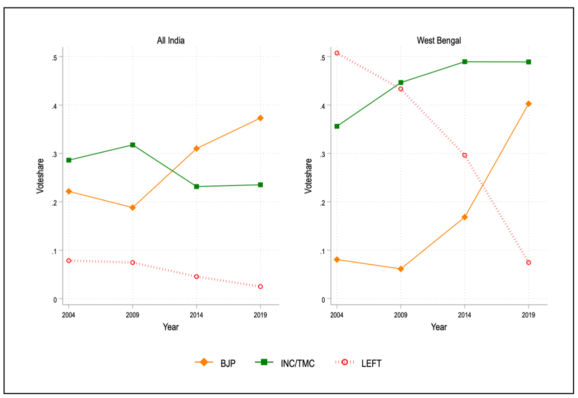
Table A4: Targeting of State and Central Benefits. Likelihood of Receiving Benefits of each Type by Predicted Income Quantile

	(1)	(2)	(3)	(4)
Panel A: Central Benefits 2014–2018	In-House Toilet		LPG Subsidy	
	Likelihood of Receiving	Cumulative Proportion	Likelihood of Receiving	Cumulative Proportion
Q1	0.215***	0.444	0.262***	0.498
	(0.025)		(0.026)	
Q2	0.145***	0.856	0.126***	0.838
	(0.024)		(0.017)	
Q3	0.055***	0.961	0.087***	0.970
	(0.015)		(0.018)	
Constant	0.033***		0.027***	
	(0.011)		(0.008)	
R-squared	0.047		0.061	
Panel B: State Benefits 2014–2018	NREGS Employment		BPL Card	
	Likelihood of Receiving	Cumulative Proportion	Likelihood of Receiving	Cumulative Proportion
Q1	0.436***	0.397	0.538***	0.476
	(0.040)		(0.036)	
Q2	0.236***	0.753	0.229***	0.796
	(0.035)		(0.026)	
Q3	0.179***	0.914	0.202***	0.949
	(0.029)		(0.025)	
Constant	0.217***		0.106***	
	(0.033)		(0.020)	
R-squared	0.088		0.147	
Panel C: State Benefits 2010–2013	NREGS Employment		BPL Card	
	Likelihood of Receiving	Cumulative Proportion	Likelihood of Receiving	Cumulative Proportion
Q1	0.082**	0.287	0.053***	0.462
	(0.040)		(0.013)	
Q2	0.065*	0.646	0.030***	0.834
	(0.034)		(0.009)	
Q3	0.090***	0.841	0.017**	0.960
	(0.027)		(0.007)	
Constant	0.460***		0.008*	
	(0.035)		(0.004)	
R-squared	0.004		0.010	
Number of Observations	3,500		3,500	

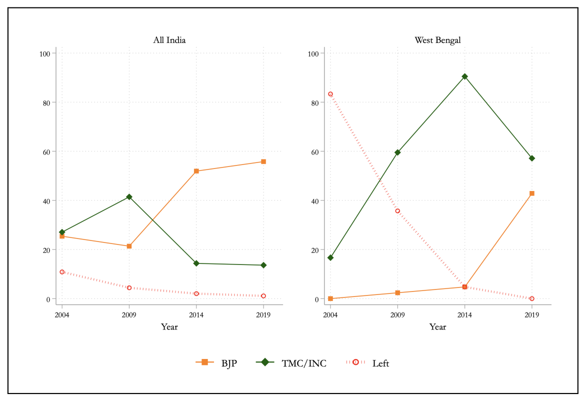
Notes: OLS regression results presented. Columns 2 and 4 present the proportion accruing to households owning below the specified predicted income quantile. Omitted category: households in the highest income quantile. Note that the Proportion (accruing) to the relevant income quantile j is given by $\frac{\omega_j \gamma_j}{\sum_j \omega_j \gamma_j}$, where γ_j is the estimated likelihood of receiving the benefit by a household in income quantile j and ω_j is the proportion of sample households in income quantile j. Predicted Income Quantiles computed using the predicted value of income from regression results presented in Table A2. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Figure A3: Vote Shares and Seat Shares of Different Parties in Parliamentary Elections. All India and West Bengal. 2004–2019

Panel A: Vote Shares

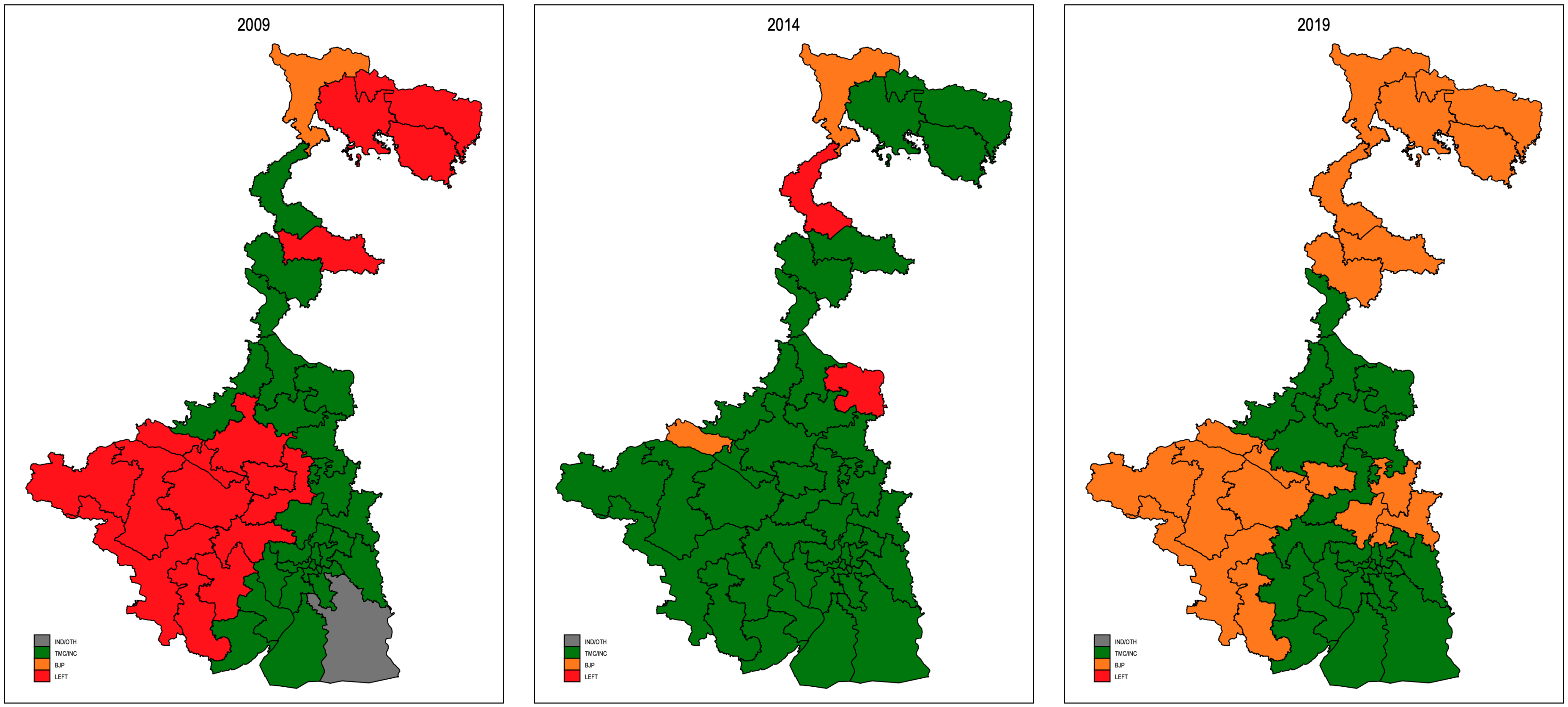


Panel B: Seat Shares



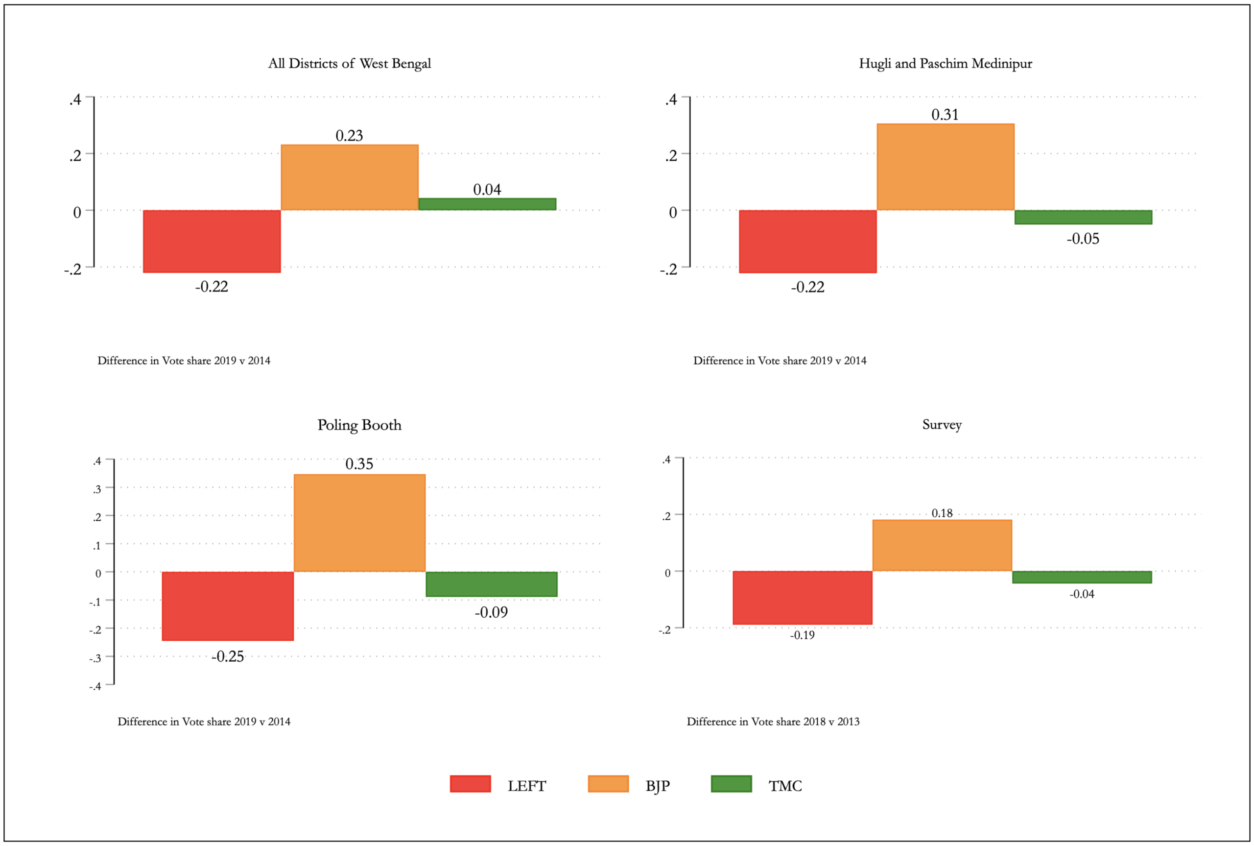
Notes: Vote share of a particular party defined as a number of votes received by all candidates of the party in a particular election as a proportion of total number valid votes cast in the particular election. Seat share of a particular party is defined as the number of seats won by the party as a proportion of the total number of seats (543 for All India and 42 for West Bengal).

Figure A4: West Bengal National Parliamentary Election Results: 2009–2019



Notes: In each election year, constituencies are colored to indicate the political party that won the seat in the first-past-the-post parliamentary elections.

Figure A5: Vote Shares Changes at Different Levels



Notes: The bottom right panel presents the changes between 2013 and 2018 survey rounds in the vote shares from our straw poll. The bottom left panel presents corresponding changes in the vote shares in the actual 2014 and 2019 elections, obtained by aggregating the shares from the official electoral results across all the polling booths that correspond to the sample villages. In the top right panel we plot the changes in the actual vote shares in the two districts where the sample villages are located; in the top left panel we plot changes in the state of West Bengal. Polling booth data are taken from the Form 20 data published by the Election Commission of India.

Table A5: Post-2013 Economic Circumstances, Benefits Received and Voting in 2018

	Vote TMC		Vote BJP	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Decline in Potato Value-Added	0.018	0.377	0.010	-0.285
	(0.055)	(0.497)	(0.045)	(0.432)
Decline in Employment Income	-0.026	0.150	0.022	0.064
	(0.034)	(0.168)	(0.029)	(0.136)
State Benefits 2014–2018	0.048**	0.130	-0.032**	-0.071
	(0.018)	(0.090)	(0.016)	(0.078)
Decline in Potato Value-Added × State Benefits	-0.012	-0.302	0.000	0.162
	(0.025)	(0.278)	(0.019)	(0.224)
Decline in Employment Income × State Benefits	0.017	-0.028	-0.020	-0.033
	(0.017)	(0.104)	(0.015)	(0.092)
Central Benefits 2014–2018	0.015	0.152	0.015	0.090
	(0.029)	(0.211)	(0.025)	(0.197)
Decline in Potato Value-Added × Central Benefits	0.005	0.144	-0.032	0.063
	(0.054)	(0.604)	(0.048)	(0.484)
Decline in Employment Income × Central Benefits	-0.012	-0.245	0.020	-0.023
	(0.026)	(0.260)	(0.025)	(0.251)
Constant	0.441***	0.271*	0.366***	0.419***
	(0.076)	(0.157)	(0.064)	(0.135)
Number of Observations	3,500	3,500	3,500	3,500
R-squared	0.051	-0.029	0.064	0.018
Effect of Receiving State Benefits for Households Experiencing:				
Decline in Potato Value-Added	0.0354	-0.172	-0.0318	0.0908
	(0.0280)	(0.253)	(0.0237)	(0.198)
Decline in Employment Income	0.0652***	0.102***	-0.0519***	-0.104***
	(0.00902)	(0.0344)	(0.00870)	(0.0287)
Effect of Receiving Central Benefits for Households Experiencing:				
Decline in Potato Value-Added	0.0194	0.296	-0.0169	0.153
	(0.0570)	(0.589)	(0.0462)	(0.497)
Decline in Employment Income	0.00224	-0.0936	0.0356**	0.0665
	(0.0203)	(0.107)	(0.0166)	(0.0948)

Notes: Regressions also control for characteristics of the household head (gender, education, age, occupation), household size, landholding, identity of household (gender of head, caste, religion, migrant status) and Hugli resident. In columns 2 and 3, IV regression results are presented. The benefits variables are instrumented by the "leave out" instrument described in the text. Employment income and Potato Value added in real terms (using the All India Price Index Number for Agricultural Labourer, General Index, $1986-87 = 100$). Employment Income and Potato value added in Rs. ('0000). Change in employment income = Employment income (2018) – Employment income (2010–2013). Change in potato value-added = Potato value-added (2018) – Potato value-added (2010–2013). Decline in Employment income = Change in Employment income < 0. Decline in Potato value-added = Change in Potato value-added < 0. Standard errors, clustered at the village level in parentheses. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A6: Voting Patterns in 2018 and 2013: Interactions between Benefits Received and GP Incumbent

	Voting in 2018			Voting in 2013		
	TMC	BJP	Left	TMC	BJP	Left
	(1)	(2)	(3)	(4)	(5)	(6)
TMC GP (2013 GP Elections)	-0.056	0.137***	-0.031			
	(0.089)	(0.039)	(0.066)			
Central Benefits 2014–2018	0.051	0.020	-0.043			
	(0.067)	(0.030)	(0.037)			
Central Benefits 2014—2018 × TMC GP	-0.047	0.007	0.040			
	(0.071)	(0.035)	(0.038)			
State Benefits 2014–2018	0.032	-0.024***	0.018			
	(0.062)	(0.008)	(0.049)			
State Benefits 2014—2018 × TMC GP	0.029	-0.024**	-0.027			
	(0.063)	(0.011)	(0.049)			
Left GP (2008 GP Elections)				0.082**	0.003	-0.104***
				(0.037)	(0.016)	(0.037)
State Benefits 2010–2013				0.114***	-0.025*	-0.104***
				(0.024)	(0.014)	(0.023)
State Benefits 2010—2013 × Left GP				-0.103***	0.029**	0.081***
				(0.026)	(0.014)	(0.024)
Constant	0.481***	0.249***	0.106	0.456***	0.045	0.487***
	(0.105)	(0.061)	(0.071)	(0.063)	(0.027)	(0.058)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.051	0.067	0.027	0.374	0.064	0.282
Total Effect of:						
State Benefits 2014—2018 in TMC GP	0.0609***	-0.0485***	-0.0089*			
	(0.0097)	(0.0093)	(0.0047)			
Central Benefits 2014—2018 in TMC GP	0.0039	0.0277	-0.0035			
	(0.0202)	(0.0166)	(0.00935)			
State Benefits 2010—2013 in Left GP				0.0109	0.0040	-0.0231**
				(0.0102)	(0.00358)	(0.0113)

Notes: In columns 1–3 the dependent variables are support for TMC, BJP and the Left as elicited in the 2018 survey, and in columns 4–6 they are as elicited in the 2013 survey. OLS Regression results presented. Regressions also control for religion, caste and the migration status of household, gender, marital status, education and occupation of the household head, household size and and indicator for residence in Hugli district. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$.

Table A7: Voting for BJP in 2018. Accounting for Shy BJP Voters

	OLS	IV
	(1)	(2)
Central Benefits 2014–2018	0.003	0.042
	(0.017)	(0.048)
State Benefits 2014–2018	-0.050***	-0.076***
	(0.009)	(0.021)
Number of Observations	3,500	3,500
R-squared	0.041	0.035
Average: No Central Benefits	0.327	
Average: No State Benefits	0.349	
First Stage F		
Central Benefits		74.52
		[0.00]
State Benefits		68.06
		[0.00]
Anderson-Rubin ($\chi^2(30)$)		54.77
		[0.00]

Notes: Voters who refused to participate in the straw poll in 2018 categorized as shy BJP voters.The benefits variables are instrumented by the "leave out" instrument described in the text. Regressions also control for religion, caste, migration status, gender, marital status, education and occupation of the household head, household size and an indicator for residence in Hugli district. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. p-values in square brackets.

Table A8: Effect of Major State and Central Benefits on Voting

	Vote TMC		Vote BJP		First Stage F
	OLS (1)	IV (2)	OLS (3)	IV (4)	(5)
Panel A: Voting in 2018					
Central Benefits 2014–2018					
In-House Toilet	0.037	0.022	0.037	0.079	405.10
	(0.033)	(0.133)	(0.034)	(0.138)	[0.000]
LPG Subsidy	0.040	0.071	-0.030	-0.129	609.59
	(0.031)	(0.142)	(0.028)	(0.123)	[0.000]
State Benefits 2014–2018					
NREGS Employment	0.114***	0.224***	-0.058**	-0.201***	342.03
	(0.028)	(0.077)	(0.024)	(0.068)	[0.000]
BPL Card	0.025	0.072	-0.021	-0.106	92.02
	(0.026)	(0.094)	(0.024)	(0.092)	[0.000]
Number of Observations	3,500	3,500	3,500	3,500	
R-squared	0.039	0.025	0.049	0.004	
Panel B: Voting in 2013					
State Benefits 2010–2013					
NREGS Employment	0.120***	0.194***	0.009	0.044**	291.18
	(0.020)	(0.053)	(0.008)	(0.021)	[0.000]
BPL Card	-0.022	0.267	0.038	-0.136	117.29
	(0.047)	(0.179)	(0.033)	(0.084)	[0.000]
Number of Observations	3,500	3,500	3,500	3,500	
R-squared	0.384	0.365	0.063	0.034	

Notes: Dependent variable voting for TMC (Columns 1 and 2) and BJP (Columns 3 and 4). IV regressions use the *Leave out* instrument. Regressions also control for religion, caste and migration status of household, gender, marital status, education and occupation of household head, household size, whether the household is a swing voter and whether household resides in Hugli. Standard errors, clustered at the Village level in parentheses. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A9: Predicted Effect of Major Central and State Benefits on Voting

	Mean (Q)	Unit Effect† TMC (β^b_{TMC})	BJP (β^b_{BJP})	Total Effect‡ TMC ($Q \times \beta^{t,b}_{TMC}$)	BJP ($Q \times \beta^{t,b}_{BJP}$)
	(1)	(2)	(3)	(4)	(5)
Central Benefits 2014–2018					
In-House Toilet	0.155	0.022	0.079	0.003	0.012
LPG Subsidy	0.161	0.071	-0.129	0.011	-0.021
State Benefits 2014–2018					
NREGS Employment	0.455	0.224	-0.201	0.102	-0.091
BPL Card	0.374	0.072	-0.106	0.027	-0.040
State Benefits 2010–2013					
NREGS Employment	0.523	0.194	0.044	0.101	0.023
BPL Card	0.036	0.267	-0.136	0.010	-0.005
Predicted Effect					
In-House Toilet				0.003	0.012
LPG Subsidy				0.011	-0.021
NREGS Employment				0.000	-0.114
BPL Card				-0.002	0.016
Predicted Effect. Top 2 state and central benefits					
Central Benefits				0.015	-0.009
State Benefits				-0.001	-0.099
Actual Change in Vote Share				-0.05	0.18

Notes: †: Unit effect on vote shares; ‡: Total effect on vote shares. Predicted Change in vote share for party p (Π^p) is given by $\sum_b (Q^b \beta_p^{2018,b} - Q^b \beta_p^{2013,b})$ aggregated over state or central benefits. There were no central benefits in 2013.

Table A10: Impact of Benefits on Votes for Different Land categories

	TMC				BJP			
	Landless	Landholding 0–0.5 acres	Landholding 0.5–1.0 acres	Landholding > 1.0 acres	Landless	Landholding 0–0.5 acres	Landholding 0.5–1.0 acres	Landholding > 1.0 acres
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vote 2018								
Central Benefits 2014–2018	-0.028	0.014	0.012	0.030	0.028	0.032	0.035	0.002
	(0.032)	(0.025)	(0.033)	(0.040)	(0.024)	(0.021)	(0.025)	(0.034)
State benefits 2014–2018	0.057***	0.067***	0.053***	0.045*	-0.053***	-0.047***	-0.047***	-0.034
	(0.017)	(0.010)	(0.016)	(0.025)	(0.014)	(0.010)	(0.015)	(0.021)
Number of Observations	681	1,399	804	616	681	1,399	804	616
R-squared	0.069	0.069	0.048	0.044	0.115	0.068	0.057	0.072
Vote 2013								
State benefits 2010–2013	0.021	0.009	0.047**	0.023	0.009	0.005	-0.009	0.001
	(0.019)	(0.012)	(0.018)	(0.023)	(0.010)	(0.005)	(0.007)	(0.011)
Number of Observations	681	1,399	804	616	681	1,399	804	616
R-squared	0.414	0.412	0.306	0.313	0.080	0.056	0.072	0.100

Notes: OLS regressions presented. Regressions also control for religion, caste and migration status of household, gender, marital status, education and occupation of household head, household size, whether the household is a swing voter and whether the household resides in Hugli. Standard errors clustered at the village level in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A11: Benefits by Landholding Category and Predicted Impact on Votes

	Land Category	Mean (Q)	Unit Effect† TMC $\beta^{t}_{TMC,j}$	BJP $\beta^{t}_{BJP,j}$	Total Effect‡ TMC $(Q \times \beta^{t,b}_{TMC,j})$	BJP $(Q \times \beta^{t,b}_{BJP,j})$
		(1)	(2)	(3)	(4)	(5)
Central Benefits 2014–2018	Landless	0.738	-0.034	0.045	-0.025	0.033
	Landholding 0–0.5 acres	0.610	0.0137	0.0322	0.008	0.020
	Landholding 0.5–1.0 acres	0.443	0.0123	0.0354	0.005	0.016
	Landholding > 1.0 acres	0.312	0.0304	0.00235	0.009	0.001
State Benefits 2014 – 2018	Landless0	2.147	0.0573	-0.0534	0.123	-0.115
	Landholding 0–0.5 acres	2.105	0.0670	-0.0467	0.141	-0.098
	Landholding 0.5–1.0 acres	1.473	0.0528	-0.0474	0.078	-0.070
	Landholding > 1.0 acres	1.122	0.0451	-0.0344	0.051	-0.039
State Benefits 2010 – 2013	Landless0	1.341	0.0209	0.00927	0.028	0.012
	Landholding 0–0.5 acres	1.237	0.00925	0.00542	0.011	0.007
	Landholding 0.5–1.0 acres	1.062	0.0470	-0.00896	0.050	-0.010
	Landholding > 1.0 acres	0.969	0.0230	0.000600	0.022	0.001
Predicted Effect on Change in Vote Shares						
Central Benefits $(\frac{1}{n}\sum_j (Q \times \beta^{b2018}_{p,j})$					0.001	0.014
State Benefits $(\frac{1}{n}\sum_j Q \times \beta^{b2018}_{p,j} - \frac{1}{n}\sum_j Q \times \beta^{b2013}_{p,j})$					0.070	-0.083
Total Predicted effect of Benefits (Central + State)					0.071	-0.069
Actual Change					-0.05	0.18

Notes: †: Unit effect on vote shares; ‡: Total effect on vote shares. Estimated coefficients ($\beta^{t}_{TMC,j}$ and $\beta^{t}_{BJP,j}$) presented in Table A12. j denotes predicted income quartile (computed using the predicted value of income from regression results presented in Table A2); b denotes the benefit type (state/central); t denotes year (2013, 2018).

Table A12: Impact of Benefits on Votes for Different Income Quartiles

	TMC				BJP			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vote 2018								
Central Benefits 2014–2018	-0.034	0.002	0.055	0.073*	0.045**	0.028	0.029	-0.013
	(0.027)	(0.024)	(0.039)	(0.037)	(0.022)	(0.023)	(0.029)	(0.025)
State Benefits 2014–2018	0.074***	0.058***	0.041*	0.051**	-0.057***	-0.053***	-0.040*	-0.023
	(0.012)	(0.014)	(0.021)	(0.025)	(0.011)	(0.012)	(0.020)	(0.019)
Number of Observations	968	1,251	649	632	968	1,251	649	632
R-squared	0.072	0.057	0.072	0.057	0.099	0.068	0.075	0.040
Vote 2013								
State Benefits 2010–2013	0.018	0.024*	0.015	0.037*	0.009	0.001	0.003	-0.012
	(0.014)	(0.014)	(0.017)	(0.022)	(0.006)	(0.006)	(0.009)	(0.009)
Number of Observations	968	1,251	649	632	968	1,251	649	632
R-squared	0.395	0.340	0.418	0.363	0.072	0.074	0.074	0.087

Notes: OLS regressions presented. Regressions also control for religion, caste and migration status of household, gender, marital status, education and occupation of household head, household size, whether the household is a swing voter and whether the household resides in Hugli. Predicted Income Quartiles computed using the predicted value of income from regression results presented in Table A2. Standard errors clustered at the village level in parentheses. Significance: $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table A13: Benefits by Income Quantiles and Predicted Impact on Votes

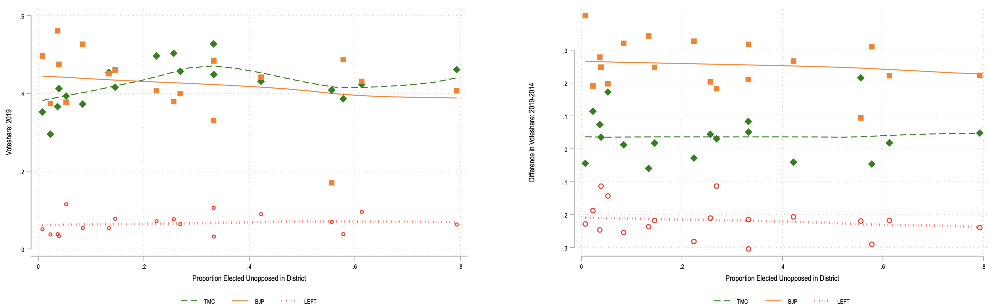
	Predicted Income Quartile	Mean (Q)	Unit Effect[†] TMC $\beta^t_{TMC,j}$	BJP $\beta^t_{BJP,j}$	Total Effect[‡] TMC $(Q \times \beta^{t,b}_{TMC,j})$	BJP $(Q \times \beta^{t,b}_{BJP,j})$
		(1)	(2)	(3)	(4)	(5)
Central Benefits 2014–2018	1	0.738	-0.034	0.045	-0.025	0.033
	2	0.530	0.002	0.028	0.001	0.015
	3	0.481	0.055	0.029	0.026	0.014
	4	0.291	0.073	-0.013	0.021	-0.004
State Benefits 2014 – 2018	1	2.532	0.074	-0.057	0.187	-0.144
	2	1.864	0.058	-0.053	0.108	-0.099
	3	1.525	0.041	-0.04	0.063	-0.061
	4	0.805	0.051	-0.023	0.041	-0.019
State Benefits 2010 – 2013	1	1.393	0.018	0.009	0.025	0.013
	2	1.203	0.024	0.001	0.029	0.001
	3	1.037	0.015	0.003	0.016	0.003
	4	0.899	0.037	-0.012	0.033	-0.011
Predicted Effect on Change in Vote Shares						
Central Benefits $(\frac{1}{n}\sum_j (Q \times \beta^{b2018}_{p,j})$					0.006	0.015
State Benefits $(\frac{1}{n}\sum_j Q \times \beta^{b2018}_{p,j} - \frac{1}{n}\sum_j Q \times \beta^{b2013}_{p,j})$					0.074	-0.082
Total Predicted effect of Benefits (Central + State)					0.080	-0.068
Actual Change					-0.05	0.18

Notes: [†]: Unit effect on vote shares; [‡]: Total effect on vote shares. Estimated coefficients ($\beta^t_{TMC,j}$ and $\beta^t_{BJP,j}$) presented in Table A12. j denotes predicted income quartile (computed using the predicted value of income from regression results presented in Table A2); b denotes the benefit type (state/central); t denotes year (2013, 2018).

Figure A6: Unopposed Seats in 2018 GP Elections and 2019 Vote shares

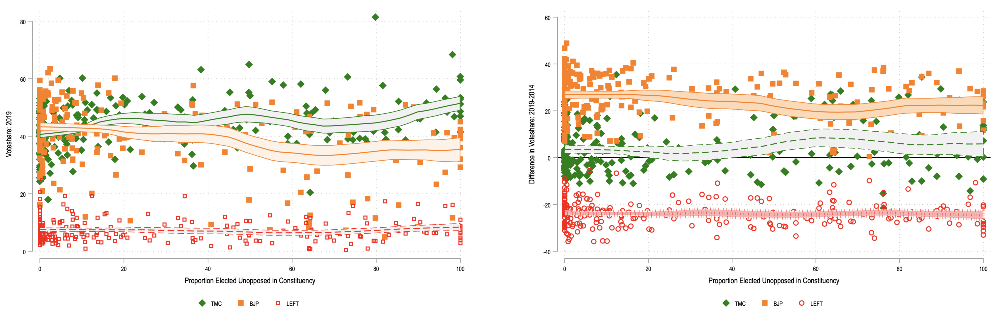
Panel A: District Level

Vote Shares 2019 | Change in Vote Shares (2019–2014)



Panel B: Assembly Constituency Level

Vote Shares 2019 | Change in Vote Shares (2019–2014)



Notes: Locally weighted polynomial regressions and 90% confidence interval presented. Data includes all parliamentary election constituencies in West Bengal.

Table A14: Voting Patterns in 2018 and 2013: Interactions between Benefits and Household Characteristics

	Vote for party in 2018		Vote for party in 2013	
	TMC	BJP	TMC	BJP
	(1)	(2)	(3)	(4)
Non Hindu Household	0.236***	-0.181***	-0.000	-0.044**
	(0.048)	(0.041)	(0.034)	(0.017)
Recent Migrant Household	0.164	0.063	0.352**	-0.013
	(0.332)	(0.312)	(0.141)	(0.028)
Non Hindu × Recent Migrant	0.172	-0.202	0.144	0.024
	(0.236)	(0.226)	(0.156)	(0.032)
SC Household	-0.033	0.084*	-0.017	-0.022
	(0.047)	(0.046)	(0.038)	(0.015)
ST Household	-0.113	0.060	0.011	-0.070***
	(0.119)	(0.106)	(0.089)	(0.025)
State Benefits	0.062***	-0.038***	0.038**	-0.001
	(0.014)	(0.012)	(0.015)	(0.005)
Non Hindu Household × State Benefits	-0.036*	0.023	0.000	0.000
	(0.018)	(0.014)	(0.025)	(0.009)
Recent Migrant Household × State Benefits	0.009	-0.053	-0.261***	-0.006
	(0.093)	(0.084)	(0.074)	(0.015)
SC Household × State Benefits	0.008	-0.034**	-0.047**	0.008
	(0.017)	(0.016)	(0.019)	(0.007)
ST Household × State Benefits	-0.012	-0.009	-0.004	0.023
	(0.041)	(0.036)	(0.047)	(0.015)
Central Benefits	0.014	0.022		
	(0.024)	(0.021)		
Non Hindu Household × Central Benefits	0.013	-0.022		
	(0.041)	(0.030)		
Recent Migrant Household × Central Benefits	0.128	-0.094		
	(0.089)	(0.080)		
SC Household × Central Benefits	-0.033	0.033		
	(0.033)	(0.030)		
ST Household × Central Benefits	0.029	-0.020		
	(0.078)	(0.055)		
Constant	0.510***	0.323***	0.455***	0.051*
	(0.070)	(0.064)	(0.056)	(0.026)
Number of Observations	3,500	3,500	3,500	3,500
R-squared	0.052	0.067	0.374	0.062
Effect of Receiving State Benefits on voting for party				
Non Hindu Household	0.0263*	-0.0150	0.0377*	-0.000791
	(0.0133)	(0.00997)	(0.0226)	(0.00710)
Recent Migrant Household	0.0712	-0.0909	-0.223***	-0.00697
	(0.0898)	(0.0825)	(0.0748)	(0.0140)
Non Hindu × Recent Migrant	0.0619***	-0.0381***	0.0377**	-0.00106
	(0.0135)	(0.0121)	(0.0146)	(0.00508)
SC Household	0.0703***	-0.0720***	-0.00931	0.00741
	(0.0134)	(0.0128)	(0.0124)	(0.00507)
ST Household	0.0496	-0.0473	0.0335	0.0217
	(0.0403)	(0.0345)	(0.0451)	(0.0164)
Effect of Receiving Central Benefits on voting for party				
Non Hindu Household	0.0268	-3.39e-05		
	(0.0351)	(0.0217)		

Continued ...

Voting Patterns in 2018 and 2013: Interactions between Benefits and Household Characteristics (Continued)

	Vote for party in 2018		Vote for party in 2013	
	TMC	BJP	TMC	BJP
	(1)	(2)	(3)	(4)
Recent Migrant Household	0.142	-0.0723		
	(0.0906)	(0.0834)		
Non Hindu × Recent Migrant	0.0138	0.0218		
	(0.0244)	(0.0212)		
SC Household	-0.0189	0.0550**		
	(0.0312)	(0.0265)		
ST Household	0.0425	0.00132		
	(0.0751)	(0.0510)		

Notes: The dependent variables are support for TMC and BJP as elicited in the 2018 survey (columns 1 and 2), and as elicited in the 2013 survey (columns 3 and 4). OLS Regression results presented. Regressions also control for gender, marital status, education and occupation of the household head, household size and and indicator for residence in Hugli district. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A15: Benefits Received by Household Characteristics

	State Benefits 2010–2013		State Benefits 2014–2018		Central Benefits 2014–2018	
	OLS (1)	VFE (2)	OLS (3)	VFE (4)	OLS (5)	VFE (6)
Non Hindu Household	-0.065	0.058	-0.350*	0.056	0.020	-0.006
	(0.126)	(0.117)	(0.176)	(0.118)	(0.074)	(0.071)
Recent Migrant Household	-0.334	-0.143	-0.463**	0.095	-0.258	-0.191
	(0.213)	(0.217)	(0.204)	(0.181)	(0.163)	(0.163)
Non Hindu × Recent Migrant	-0.885***	-0.556**	0.333	-2.353***	0.040	-0.728***
	(0.249)	(0.244)	(0.276)	(0.236)	(0.178)	(0.167)
SC Household	0.183**	0.194***	0.665***	0.718***	0.236***	0.199***
	(0.090)	(0.060)	(0.148)	(0.072)	(0.053)	(0.047)
ST Household	0.162	0.328**	0.401	0.643***	0.083	0.078
	(0.170)	(0.136)	(0.254)	(0.147)	(0.109)	(0.097)
Landless	0.364***	0.331***	0.441***	0.598***	0.117**	0.157***
	(0.081)	(0.056)	(0.122)	(0.083)	(0.050)	(0.046)
Landholding 0—0.5 acres	0.201***	0.240***	0.467***	0.473***	0.129***	0.156***
	(0.063)	(0.040)	(0.092)	(0.054)	(0.034)	(0.033)
Landholding 0.5—1 acres	0.055	0.066	0.182**	0.206***	0.079***	0.070**
	(0.046)	(0.042)	(0.078)	(0.056)	(0.030)	(0.031)
Kuchha House	0.101*	0.089**	0.335***	0.254***	0.151***	0.141***
	(0.052)	(0.037)	(0.084)	(0.050)	(0.034)	(0.031)
Constant	0.774***	0.605***	1.230***	0.750***	-0.022	0.082
	(0.134)	(0.096)	(0.212)	(0.093)	(0.072)	(0.062)
Number of Observations	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.079	0.309	0.266	0.529	0.100	0.239

Notes: OLS regression results presented. Columns marked VFE include village fixed effects. Regressions also control for household size and characteristics of the household head (marital status, educational attainment and occupation, swing voter, Hugli residence). Recent migrant denotes households where the head was not born in the village but migrated less than 10 years previously. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B1: First Stage Regression Results. Central and State Benefits Received

	Central Benefits 2014–2018 (1)	State Benefits 2014–2018 (2)	State Benefits 2010–2013 (3)
Male Headed Household	-4.921	-4.820	-0.583
	(6.215)	(12.160)	(0.752)
Non Hindu Household	2.003	1.053	0.356
	(4.570)	(8.431)	(0.353)
Recent Migrant Household	-4.539***	3.665***	1.731
	(0.685)	(0.988)	(1.349)
Non Hindu × Recent Migrant	-0.392	-2.416***	-0.700**
	(0.290)	(0.571)	(0.292)
SC Household	4.323*	-0.914	0.795**
	(2.365)	(5.898)	(0.352)
ST Household	4.574	4.545	1.912*
	(5.093)	(7.879)	(1.030)
Household Size	-0.365	0.323	-0.003
	(0.352)	(0.604)	(0.037)
Head Married	6.566	-10.013	0.381
	(4.078)	(6.783)	(0.444)
Head: More than Primary Schooling	-3.808**	-2.256	0.219
	(1.770)	(3.373)	(0.225)
Head: Occupation Cultivation	1.520	3.381	0.759**
	(2.675)	(3.288)	(0.328)
Head: Occupation Labour	5.274	11.164**	0.299
	(3.304)	(4.403)	(0.393)
Landless	6.736*	0.461	1.066***
	(3.622)	(6.833)	(0.379)
Landholding 0—0.5 acres	6.773**	0.837	0.814***
	(3.151)	(4.282)	(0.260)
Landholding 0.5—1.0 acres	4.425	0.077	0.580**
	(2.871)	(4.592)	(0.276)
Swing Voter Household	-0.648	-1.088	-0.072
	(1.632)	(3.372)	(0.292)
$\bar{C}_{-j}$	-0.528***	-0.061	
	(0.099)	(0.303)	
Male Headed Household $\times\bar{C}_{-j}$	0.110	0.085	
	(0.142)	(0.280)	
Non Hindu Household $\times\bar{C}_{-j}$	-0.046	-0.018	
	(0.108)	(0.200)	
Recent Migrant Household $\times\bar{C}_{-j}$	0.185***	-0.152***	
	(0.026)	(0.036)	
SC Household $\times\bar{C}_{-j}$	-0.091*	0.036	
	(0.053)	(0.133)	
ST Household $\times\bar{C}_{-j}$	-0.088	-0.073	
	(0.114)	(0.182)	
Household Size $\times\bar{C}_{-j}$	0.008	-0.008	
	(0.008)	(0.014)	
Head Married $\times\bar{C}_{-j}$	-0.147	0.233	
	(0.091)	(0.153)	
Head: More than Primary Schooling $\times\bar{C}_{-j}$	0.084**	0.053	
	(0.041)	(0.078)	
Head: Occupation Cultivation $\times\bar{C}_{-j}$	-0.033	-0.071	
	(0.061)	(0.078)	
Head: Occupation Labour $\times\bar{C}_{-j}$	-0.121	-0.241**	
	(0.074)	(0.101)	

Continued . . .

First Stage Regression Results Central and State Received (Continued)

	Central Benefits 2014–2018 (1)	State Benefits 2014–2018 (2)	State Benefits 2010–2013 (3)
Landless $\times\bar{C}_{-j}$	-0.148*	0.013	
	(0.082)	(0.156)	
Landholding 0—0.5 acres $\times\bar{C}_{-j}$	-0.154**	-0.014	
	(0.071)	(0.099)	
Landholding 0.5—1.0 acres $\times\bar{C}_{-j}$	-0.099	-0.004	
	(0.066)	(0.105)	
Swing Voter Household $\times\bar{C}_{-j}$	0.010	0.021	
	(0.037)	(0.076)	
$\bar{S}_{-j}$	0.050**	-0.726***	-0.665***
	(0.021)	(0.067)	(0.023)
Male Headed Household $\times\bar{S}_{-j}$	0.022	0.027	0.007
	(0.029)	(0.056)	(0.013)
Non Hindu Household $\times\bar{S}_{-j}$	-0.009	-0.006	-0.006
	(0.020)	(0.037)	(0.006)
Recent Migrant Household $\times\bar{S}_{-j}$			-0.082*
			(0.048)
SC Household $\times\bar{S}_{-j}$	-0.021	0.006	-0.011*
	(0.011)	(0.028)	(0.006)
ST Household $\times\bar{S}_{-j}$	-0.025	-0.024	-0.028*
	(0.025)	(0.037)	(0.016)
Household Size $\times\bar{S}_{-j}$	0.002	-0.002	0.000
	(0.002)	(0.003)	(0.001)
Head Married $\times\bar{S}_{-j}$	-0.029	0.047	-0.005
	(0.019)	(0.032)	(0.008)
Head: More than Primary Schooling $\times\bar{S}_{-j}$	0.018**	0.007	-0.005
	(0.008)	(0.016)	(0.004)
Head: Occupation Cultivation $\times\bar{S}_{-j}$	-0.007	-0.014	-0.010*
	(0.012)	(0.015)	(0.006)
Head: Occupation Labour $\times\bar{S}_{-j}$	-0.023	-0.049**	-0.002
	(0.016)	(0.020)	(0.007)
Landless $\times\bar{S}_{-j}$	-0.031*	-0.002	-0.013*
	(0.017)	(0.032)	(0.007)
Landholding 0—0.5 acres $\times\bar{S}_{-j}$	-0.030**	0.001	-0.010**
	(0.015)	(0.020)	(0.005)
Landholding 0.5—1.0 acres $\times\bar{S}_{-j}$	-0.020	0.003	-0.008*
	(0.013)	(0.021)	(0.005)
Swing Voter Household $\times\bar{S}_{-j}$	0.005	0.007	0.003
	(0.008)	(0.016)	(0.006)
Hugli Resident	5.856***	-26.326***	-11.618***
	(0.421)	(1.352)	(0.289)
Constant	6.892	78.518***	44.187***
	(4.302)	(13.369)	(1.453)
First Stage F	74.52	68.06	151.34
	[0.00]	[0.00]	[0.00]

Notes: First stage regression results for central and state benefits received by households presented. $\bar{C}_{-j}$ and $\bar{S}_{-j}$ denote the average number of central and state benefits received by households (during the period 2014–2018, columns 1–4 and during the period 2010–2013, columns 5–6), excluding households in the same village. p-values associated with the F-statistics presented in square brackets. Standard errors are clustered at the village level are presented in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.