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 under the BJP-led central government, welfare benefits in India have become more programmatic, less prone to clientelistic control by state and local governments and better targeted to the poor. It has also been suggested that these welfare reforms helped the BJP raise its vote share relative to competing regional incumbents. We test these hypotheses using longitudinal data from 3500 rural households in the state of West Bengal. While pro-poor targeting of pre-existing ”state” programs improved after 2014, we fail to find evidence that the new “central” programs introduced after 2014 were better targeted than the state programs. We also fail to find evidence of decline in clientelism in delivery of state programs, or in their effectiveness in generating votes for the regional incumbent (TMC). Households that received central benefits during 2014–2018 were more likely to support the BJP relative to TMC but this effect is not robust to different specifications and frequently statistically insignificant. Consequently, changes in the scale, composition and targeting of welfare programs fail to explain the observed rise in BJP's vote share. We present suggestive evidence that the BJP's growing popularity in West Bengal owed to its ideological and identity-based appeal, rather than its reforms to the welfare system.

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. These reduce scope for local discretion, and related diversion of benefits. Such changes in welfare programs have occurred in a number of low and middle income countries recently. Notable examples are the widespread adoption of conditional cash transfers in many developing countries, an electronic food voucher program (BPNT) in Indonesia and a formula-bound cash transfer program (BISP) in Pakistan. Researchers have found evidence of consequent improvements in pro-poor targeting in Indonesia (Banerjee et al., 2023) and Pakistan (Haseeb and Vyborny, 2022) and increased political competition between parties controlling the central government and clientelistic regional incumbents in Brazil and Mexico (de Jainvry et al., 2014, Larraguy et al., 2015, Frey, 2019).

It has been argued that a similar pattern has been emerging in India recently, particularly since 2014 when the Bharatiya Janata Party (BJP) was first elected with an absolute majority in the national parliament. Soon after, the BJP-led central government introduced new benefit programs such as "zero-balance" bank accounts (*Jan Dhan Yojana*), in-house toilets (*Swachh Bharat Yojana*), credit cards for farmers (*Kisan Credit Card*) and new methods of disbursing subsidies for LPG (cooking fuel – *Ujjwala Yojana*). In these schemes, eligibility is based on clearly defined verifiable criteria, online verification, and electronic transfers. The BJP government also introduced new biometric verification and other electronic mechanisms for beneficiaries of pre-existing welfare schemes such as the NREGS and public distribution system (PDS), while at the same time restricting funding for the NREGS. Scholars have argued that these changes have reduced the scope for local discretion, clientelism and corruption (Muralidharan et al., 2016, Banerjee et al., 2019, Deshpande et al., 2019, Wilkinson, 2021, Joshi et al., 2022, Muralidharan et al., 2023). They have also argued that the central government's aggressive advertising programs on both conventional and social media has allowed the BJP to successfully claim credit both for the pre-existing schemes and the new ones they introduced (Deshpande et al., 2019, Wilkinson, 2021).[1]

However, the implications of these changes to welfare programs for the targeting of the benefit distribution and for political competition are not clearly established. For instance, we are not aware of any attempt to compare the targeting performance of the new welfare programs with pre-existing programs. Although media accounts commonly attribute the popularity of the BJP and its leader Narendra Modi to the new welfare programs,[2] it has not received uniform emphasis amongst scholars. While Deshpande et al. (2019) concur with the media view, others (Jaffrelot, 2019, Chhibber and Verma, 2019) have instead emphasized the importance of identity politics, the BJP's nationalistic ideology, its strong political organization, and Narendra Modi's personal brand image in explaining the rise of the BJP vote share between 2014-19.

This paper uses data from household surveys to test these hypotheses. Specifically, we investigate how the targeting of welfare programs has changed since 2014, and how welfare program reforms have changed the vote share of the BJP vis-a-vis the regional incumbent, Trinamool Congress (TMC), in the state of West Bengal in Eastern India. West Bengal is a suitable context to study for two reasons. First, it is a state where the central and state governments were controlled by different parties after 2014. While state and local governments were dominated by the TMC both before and after 2014, the BJP emerged as a significant competitor only after 2014. Second, there is evidence of clientelistic networks operated by the TMC involving an implicit *quid pro quo* with voters exchanging benefits for votes, and opportunistic manipulation of benefit allocations to increase its vote share (Bardhan et al., 2015, 2024, Dey and Sen, 2020, Shenoy and Zimmerman, 2020, Mahadevan and Shenoy, 2023).[3]

We use data from two waves of a longitudinal survey of 3500 rural households in two districts of West Bengal. The surveys were conducted in 2013 and 2018, immediately prior to the 2014 and 2019 parliamentary elections. The surveys allow us to use households' own

[1] Auerbach et al. (2022) summarise a growing literature that questions whether Indian voters continue to exchange their votes for clientelistic transfers of goods.

[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. (New York Times Dec 4, 2023)

[3] Bhattacharyya (2009) describes West Bengal as a *"party state"*, where the state ruling party and the party machinery play an important role in the distribution of benefits.

reports of the benefits they received, and examine their association with various indicators of their socio-economic 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 booth, to gauge their support for the different political parties.[4]

Two categories of benefits programs are distinguished: new programs introduced by the BJP led central government after 2014, and programs that were started before 2014. We refer to these as 'central' and 'state' programs respectively, in accordance with the presumption that recipients of the former (respectively latter) group would be more likely to assign credit to the BJP (respectively TMC) during the 2019 election. As elaborated further in Section 3, attribution of credit for a given program is likely to depend on which party controlled the central government at the time the program was originally launched, which party currently controls the distribution of program benefits, and exposure to recent campaign advertisements. On all three counts the BJP would tend to receive a greater share of credit for the post-2014 programs relative to the pre-2014 ones. This presumption is corroborated both in the 2019 National Election Survey as well as in our empirical results.

We examine the progressivity of state and central programs by calculating benefit shares across different groups, defined by ownership of cultivable land or social status (Scheduled Castes (SCs) and Scheduled Tribes (STs)), both of which are correlated with disadvantage. When benefit receipt is measured in terms of the aggregate number of state and central benefits received, we find little difference between the progressivity of central and state programs during the period 2014–2018. When looking at individual programs, central and state programs cannot be ranked unambiguously. The (central) LPG subsidy program (Ujjwala) was more progressive than the (state) NREGS program, which in turn was more progressive than the (central) in-house toilet program (Swachh Bharat). On the other hand, while aggregate state benefits became more progressive after 2014, this was not the case for every state scheme.

To estimate the causal impact of receiving a given benefit on voting patterns, we need to confront problems of unobserved heterogeneity and endogeneity bias. We address these problems in various ways: controlling for household fixed effects, and an instrumental variable specification using a "leave one out" shift-share type of instrument for benefit distribution, based on Bardhan et al. (2024). We find that state and central benefits had

[4]Similar approaches have been used by a number of researchers: see, for example Casey (2015) in Sierra Leone, Bardhan et al. (2024) in West Bengal and the Lokniti-CSDS national election surveys all over India.

differing impacts on the vote shares of the TMC and BJP, consistent with the presumption underlying this classification of welfare programs. Households that received (pre-existing) state benefits between 2014 and 2018 became significantly more likely to vote for the TMC and less likely to vote for the BJP. In contrast, households that received central benefits became more likely to vote for the BJP (while the propensity to vote for TMC fell or remained unchanged), though these effects are often not statistically significant.

However, we fail to find evidence of weakening clientelism in the distribution of state benefits: in contrast they became more effective in raising TMC's vote share in 2018 compared to 2013. Moreover, changes in welfare programs fail to explain the changes in vote shares that took place post-2014. To predict the overall effect of changes in welfare benefits on vote shares, we calculate the combined effect of changes in the scale of state and central programs with changes in their respective effectiveness in generating votes for either party. This leads us to predict that had welfare programs not changed in either scale or effectiveness between the pre-2014 and post-2014 periods, the BJP's vote share would have declined by 13.7 percentage points, and the TMC's vote share would have increased by 8.3 points between 2013 and 2018. This is the opposite of the actual changes that took place: the TMC's vote share decreased by 4.4 percentage points and the BJP's vote share increased by 18 percentage points. We thus conclude that the increased vote share of the BJP after 2014 cannot be explained by the changing scale, composition or vote-generating effectiveness of welfare programs. This result turns out to be robust to alternative specifications. In summary, we provide compelling evidence against the presumption that central programs were better targeted than state programs, that clientelism has been declining in West Bengal, or that changes in welfare programs help explain the rise in BJP's vote share vis-a-vis the TMC after 2014.

The failure of welfare program changes to explain the rising share of the BJP can be explained as follows. First, we have already noted that state benefits became more effective in generating support for the TMC after 2014, possibly owing to a deepening and consolidation of their clientelistic ties with local voters. Second, despite the narrative to the contrary and widespread advertising attributing the program to Prime Minister Modi, local governments continued to exercise control over the distribution of both pre-existing and new welfare programs. For instance, the two targeted central programs for the LPG subsidy and in-house toilets restrict eligibility to households with BPL cards; local governments continued to be responsible for identifying which households belonged to the BPL category and issuing them cards. It is therefore possible that LPG subsidy beneficiaries attributed partial credit to the TMC. In contrast they gave BJP far less credit for pre-2014 benefits because the BJP were neither the originators of those programs, nor did they control their local distribution.

Third, indirect cross-party effects compounded the BJP's relative disadvantage. In 2013 the Left Front was the long-entrenched party and the TMC was their emerging political competitor. However, by 2018 the Left Front had been largely voted out, and the TMC was well-established but facing a growing challenge from the BJP. We estimate that if a household received an additional state benefit during 2014–2018, it became 8.5 percentage points less likely to vote for the BJP in 2018. In contrast, in 2013 receiving an additional state benefit decreased the likelihood that the household voted for the major incumbent, the Left Front, by 8.6 percentage points, and, as a by-product, *increased* the likelihood that it voted for the BJP by 1.7 points. Weighting by the scale of state benefits, these changing cross-effects implied that state benefits caused the vote share of the BJP to decline by 17.2 percentage points between 2013 and 2018, which overwhelmed the direct 3.5 percentage point boost provided by the new central benefits.

A fourth explanation is that in the face of shrinking funds released by the central government for the NREGS program and possibly in response to political competition from the BJP, the West Bengal government expanded the scale of other state programs. As a result, the overall fraction of households receiving any state benefit remained roughly unchanged (at around 75%), with more households reporting they had received BPL cards, community toilets, housing, flood relief or self-help groups.

If changes in welfare programs do not help predict the post-2014 rise in the BJP vote share in West Bengal, what does? The remainder of the paper considers some potential alternative explanations. We consider the possibility that households whose economic circumstances worsened after 2014 voted against the incumbent TMC and generated the pro-BJP wave. We find no support for this hypothesis when we measure households' economic situation based on household income from the cultivation of potatoes (the major cash crop in the area). We also find no evidence to support the alternative hypothesis that violence by TMC party activists during the village council (GP) elections immediately preceding the 2019 parliamentary elections led to a wave of sentiment against the TMC.

Instead, we find suggestive evidence that the rising support for BJP stemmed partly from its growing religious-identity-based appeal to voters. Hindu households became more likely to vote for the BJP, while the increase in support among non-Hindus was far smaller.

This difference is robust to inclusion of controls for household assets, welfare benefits received, and changes in household 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]

The rest of the paper is organized as follows. Section 2 describes the data (Section 2.1) and presents selected descriptive statistics relating to household characteristics and welfare benefits (Sections 2.2 and 2.3 respectively). Section 3 lays out the conceptual framework and the specific hypotheses that we test. Section 4 compares targeting patterns across types of benefits and over time. Section 5 describes the political context, details of the vote shares, and a range of descriptive facts about changes in voting patterns. Section 6 discusses the underlying voting model, the regression specification and details of the IV strategy. It also presents the main empirical results pertaining to impacts of benefit programs on vote shares and various robustness checks. Section 7 discusses alternative explanations for the rising BJP vote share and Section 8 concludes.

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

2.1 Data

Our data come from a longitudinal survey of a sample of 3500 households residing in 72 randomly selected villages in the potato-growing *talukas* (sub-divisions) of the Hugli and Pashchhim Medinipur 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, where we collected extensive data on the households' demographic and socio-economic characteristics, transfers they received from the government, and their engagement with civil society and political activities such

[5] Choudhary et al. (2020) contrast the 2019 parliamentary election with the one in 2014, when they argue the BJP gathered support instead by striking an "issue-based electoral chord".

[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 are restricted to these two districts as they were conducted for other unrelated projects: see Maitra et al. (2017), Mitra et al. (2018), Maitra et al. (2022, 2024). In 2011 the Census of India reported the population of Hugli as 3.4 million and of Pashchhim Medinipur as 5.2 million. In Section 5.1.1 we show that changes in vote shares in these two districts were similar to those in West Bengal as a whole.

as attending the village townhall meetings (*gram sabhas*), 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]

2.2 Household Characteristics

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

The majority of the households in our sample belonged to low socio-economic classes. This is evidenced by their low landholding: about twenty percent owned no agricultural land, and two-third owned less than one acre. Sixty percent of household heads had only a primary school education, and most were engaged in either cultivation or casual labour. More than one-half of dwellings were non-permanent (or *kuchha*), usually built of mud or tin.

Our data also allow us to compute the proportion of households that experienced a change in economic circumstances between 2013 and 2018. Since potatoes are the principal cash crop cultivated in this region, our surveys contain detailed data about incomes that households earned from cultivating potatoes (as measured by value added: potato sales revenues less cost of purchased inputs).[9] On average households experienced a 25.5% increase in the earnings from potato cultivation, while 9% of households received lower value-added from potatoes in 2018 than in 2013.

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 averages using the pooled rural sample data of the National Sample Survey from the

[7] Some households split between 2013 and 2014. We tracked all households back to the original (parent) household.

[8] These are mainly widowed women.

[9] We adjust the value-added estimate in Rs. ('0000), using the All India Price Index Number for Agricultural Labourers, General Index, 1986–87=100).

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 Potato Value-Added	0.255	0.489		
Experiencing Decline in Value-Added	0.093	0.290		

Notes: Potato Value added in real terms (using the All India Price Index Number for Agricultural Labourer, General Index, 1986–87=100). Potato value added in Rs. ('0000). Change in potato value-added = Potato value-added (2018) – Potato value-added (2010–2013). 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).

same two districts as our household survey sample, collected in 2009–2010 (66^{th} round) and 2011–2012 (68^{th} round). Unlike the NSS, our sampling frame includes only the potato-growing subdistricts in these two districts. Despite this, we find very similar proportions of scheduled castes, non-Hindus and general caste/OBC Hindus. However our sample includes a smaller percentage of scheduled tribe households, and the distribution of landholding exhibits thicker tails at both ends.[10]

[10] Occupations were categorised differently in our survey than in the NSS data, so the occupational status variable cannot be compared.

2.3 State and Central Benefits: Background and Descriptive Statistics

Of the new benefit schemes that the BJP-led central government introduced after 2014, we focus on four that were the subject of aggressive advertising campaigns featuring the Prime Minister Narenda Modi's image on billboards, television and social media. These include grants to construct in-house toilets (*Swachh Bharat Yojana*), no-fee "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 (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, pre-existing as well as 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 can influence 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). The lists of BPL households are created by local governments. Other scheme-specific eligibility requirements to restrict benefits to poor or marginal farmers, the disabled, pregnant mothers, or households with girl children imply that the local government needs to be involved in verification. While the *Ujjwala* subsidy is paid directly into the bank accounts of beneficiaries, individual state governments can decide how the *Swachh Bharat* scheme should be implemented (MDWS, 2014, page 12). Thus the ultimate delivery of the benefits continues to involve discretionary elements, similar to the pre-existing benefit schemes. Other new programs such as *Jan Dhan* accounts and *Kisan credit cards*, and pre-existing schemes such as NREGS do not restrict eligibility in this way, although whether they were truly available to all who applied for them is an empirical question.

[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.

Government information campaigns advertised these new programs as better targeted and more efficiently administered than schemes that had come before. The Central government exercised tighter control over and received more credit for these new programs. The aggressive branding of these schemes as personally attributable to Prime Minister Modi could also have led voters to attribute these schemes to the BJP and Modi himself, to a greater extent than political parties or individual politicians were identified with schemes that state-level incumbent governments had introduced previously.

As mentioned in the Introduction (and explained further in Section 3), we use the term "central benefits" to refer to these four schemes, and the term "state benefits" refers to other pre-existing welfare benefit schemes (listed in Table 2). Note that by construction, central benefits did not exist before 2014. State benefits were distributed both before and after 2014. Note that "state benefits" does not necessarily mean the state government funded the scheme. Instead we attach the label to indicate that voters may have perceived the state goverment as primarily responsible for the household receiving the benefit.

Consistent with reports of declining funds for the program after the BJP was elected to the central government (Jaffrelot, 2019), Table 2 shows that the proportion of sample households who reported they had received workfare through the NREGS decreased by 7 percentage points between 2013 and 2018. Similarly, the proportion of households who reported receiving drinking water through the local village government (*gram panchayat*, or GP) decreased by 5 percentage points. However, for all other state schemes, the fraction of beneficiaries rose. The increase is 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). The substantial increase after 2013 was the result of a thorough revamping of BPL beneficiary lists that took place around 2015, in the process of implementing the National Food Security Act (Drèze et al., 2019). 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). The participation rate in women's self-help groups increased more than three-fold, 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 state benefit (74.9 vs 76.2%, p-value of difference = 0.21).

At the same time, the number of state benefits per household increased from 1.2 during

Table 2: Receipt of Central and State Benefits during 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 2018 and mean 2013. Figures in square brackets denote the standard error of the difference. Statistical significance of this difference computed using t-test. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

2010–2013 to 1.8 in 2014–2018 (see Panel C of Table 2, p-value of difference = 0.00). 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 15–19% of sample households. Thus after 2014, central benefits were rolled out to less than one-half of sample households, as compared to three out of four households that received state benefits. Despite its reduced coverage, the NREGS scheme continued to account for more beneficiaries than all four central schemes combined.

3 Conceptual Framework and Hypotheses Tested

Why should we expect the BJP-led central government's new programs to be targeted differently than the pre-existing welfare programs? Why should recipients respond differently to the two categories of benefits? Why should the targeting of pre-existing programs change after 2014, and why should voters respond differently to them? We provide a conceptual framework to organize our analysis of how changes in the composition and administration of welfare programs may have impacted targeting and voting behavior.

As mentioned above, central programs allowed local governments less scope to control how beneficiaries were selected. Also, as scholars have argued, they gave local governments less of a role in the actual delivery of benefits. Therefore, they may be expected to be less vulnerable to local elite capture, clientelism and corruption (Mookherjee, 2023). As discussed in Section 1, the new delivery mechanisms and the reduced reliance on local intermediaries may also have decreased local clientelistic control and corruption in pre-existing programs. Accordingly, we test the following hypotheses related to targeting performance:

Hypothesis T1 *After 2014, central programs were better targeted to poor households and underprivileged minorities than state programs.*

Hypothesis T2 *After 2014, state programs became better targeted to the poor and underprivileged minorities than they had been previously.*

Next, why would we expect recipients to respond differently to the two categories of benefits? First, state benefits were disbursed by local governments that after 2011 were nearly all controlled by the TMC. It is likely that they targeted swing voters in an attempt to increase the TMC's vote share. To the extent that local governments had less discretion in the implementation process of central programs, and the central government was controlled by the BJP, central benefits might have been less effective at generating votes for the TMC than for other parties. Second, a range of factors likely affect how voters attribute benefit programs to different political parties – this could include which party controlled the central government when the program was first launched, which party currently controls the distribution of benefits, and exposure to advertisements and media descriptions. On all three counts the TMC was likely to receive less credit for central programs than state programs. First, the central programs were introduced when the BJP controlled the central government, whereas the state programs we consider were created under the auspices of the Congress or UPA government with which the TMC was frequently aligned. Second, the TMC-controlled local governments exercised less discretionary control over central programs than over state programs. Third, after 2014 the central government and the BJP ran aggressive media campaigns to brand the new programs as the result of Prime Minister Modi's policy actions, whereas the (pre-existing) state programs continued to retain the names and images of former Congress leaders such as Mahatma Gandhi and Indira Gandhi. The 2019 National Election Survey (NES) data corroborates this: for the country as a whole, the central government received credit for the *Ujjwala* and *Jan Dhan Yojana* schemes from more than 70% of survey respondents, for the NREGS and housing schemes from 50% of respondents, and for pensions and the foodgrain public distribution system (PDS) from about 30% of respondents (Deshpande et al., 2019, Table 4).

Similar reasons may lead one to expect that after 2014, state programs would become less effective at generating votes for the TMC: biometric verification of beneficiaries and direct deposits into bank accounts could have limited the scope for local TMC leaders to manipulate benefit distribution. Moreover, after 2014 the BJP-led central government reduced their contribution to the funding of pre-existing schemes such as the NREGS, while at the same time running advertisements claiming credit for the program. NES data show that, for the country as a whole, 50% of voters gave the central government credit for NREGS in 2019, compared to 27% in 2014(Deshpande et al., 2019, Table 4).

We therefore test the following hypotheses:

Hypothesis P1 (a) When a household received an additional central (respectively, state) benefit between 2014–2018, this increased (respectively decreased) the likelihood that it voted for the BJP in 2018;

(b) This effect of the additional central (respectively state) benefit on the likelihood that the household voted for the BJP was larger (respectively smaller) than the effect on the likelihood that it voted for the TMC;

(c) When a household received an additional central benefit it increased the chance that it voted for the BJP (respectively, TMC) by more (respectively, less) than if it had received an additional state benefit.

Hypothesis P2 (a) When a household received an additional state benefit in the period 2010–2013, it became more likely to vote for the TMC in 2013;

(b) When a household received an additional state benefit in the period 2014–2018, it became more likely to vote for the TMC in 2018;

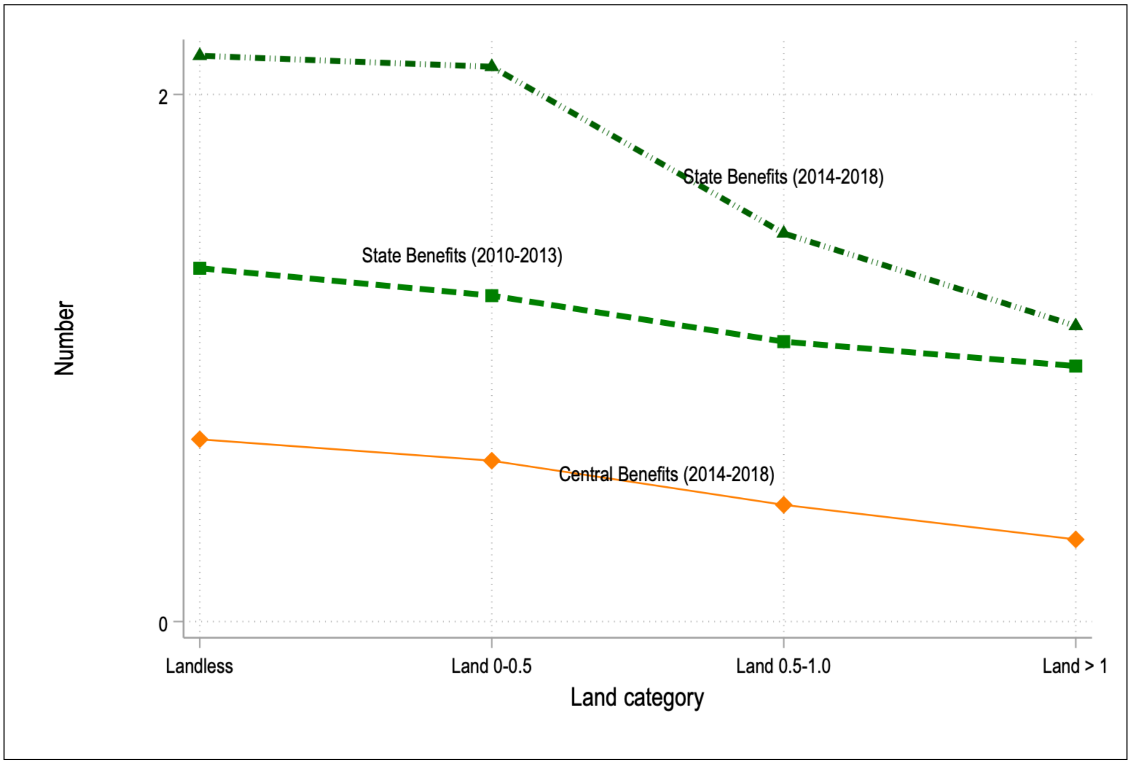
(c) Effect (b) is larger than Effect (a).

Hypothesis P3 Changes in the scale of central and state benefits and in their effectiveness in generating votes between the post-2014 and the pre-2014 periods explain the observed changes in the vote shares of the BJP and the TMC between 2014 and 2018.

4 State and Central Benefits: Comparisons of Targeting Performance

We first test Hypotheses T1 and T2, that the new central benefits were better targeted than pre-existing state benefits, and that the targeting of state benefits improved after 2013. Although we do not have the data to specifically evaluate each household's eligibility for each scheme, we can broadly assess whether households with low socio-economic status are more likely to receive the benefits. To gauge 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. In our sample 19% of households are landless, while 39%, 22% and 17% of households own 0–0.5 acres, 0.5–1.0 acres and $>$ 1.0 acres of land, respectively. Panel A of Table A1 in the Appendix shows that landholding correlates positively with education, assets, income and farming occupation of the head. In nearly 80% of landless households the head has not completed primary school, whereas only 35% of households

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



with more than 1 acres of land had heads with below primary level schooling. Sixty two percent of landless households reside in a *kuchcha* house whereas 43% for households owning more than 1 acre of land do so. Over the period 2010–2013, the average household income for households with more than 1 acre of landholding was Rs. 84328, nearly double the Rs. 39747 income of landless households.

Figure 1 plots the average number of state and central benefits received per household, in each of the four land categories. In absolute terms, households received more benefits from state schemes than central schemes, reflecting the fact that there were more state schemes in both periods, and also covered a larger number of households. As evidenced by the negative slope when we move from low to high landholding households, in both sets of schemes and in both time periods, poorer groups (those with less than 0.25 acres of landholding) received more benefits per household. However, after 2014, state benefit distribution appears to have become more progressive, as indicated by the steeper slope in the figure.[12]

[12]We check robustness using an alternative proxy of household wealth, where households are classified into different quantiles of predicted income, with predictions based on household assets and demographic characteristics. In Table A2 in the Appendix, we present results from a regression of average total household

As is standard in the literature, to measure progressivity, we calculate the implied benefit shares of the poorer groups (see for example Lanjouw and Ravallion, 1999, Alderman, 2001, Biggs et al., 2009, Kakwani et al., 2021). With more than two groups, we use the criterion of Lorenz dominance, which requires the cumulative share below each threshold to be higher in a more progressive distribution. The benefit share of group j is calculated as $\frac{\omega_j \gamma_j}{\sum_j \omega_j \gamma_j}$, where γ_j denotes the number of benefits received per household in group j and ω_j is the proportion of sample households in group j. Panel A of Figure 2 shows the implied (cumulative) benefit shares for households who owned less than the specified cultivable landholding size, separately for state and central benefits. Panel B of Figure 2 reports the benefit shares for the different social groups. Figure 2 reveals that during the period 2014–2018, those owning less land, scheduled caste (SC) and scheduled tribe (ST) households had almost identical benefit shares under both the central and state schemes – suggesting that they were equally progressive.[13] Thus, contrary to Hypothesis T1, we do not find evidence that central benefits were better targeted. On the other hand, consistent with Hypothesis T2, we find that state programs became more progressive after 2014: the shares of every disadvantaged group either increased or remained constant between 2010–2013 and 2014-2018.

When we look at specific state and central programs, we compare only those that were intended exclusively for the poor and disadvantaged: among the central schemes these include only the toilet and LPG subsidies. We compare these with the two largest state programs: NREGS and BPL card distribution. In Table 3, Panel A presents the results of OLS regression of the likelihood that a household received a particular benefit on dummies for land category. Panel B presents the implied (cumulative) benefit shares.[14]

With one exception, the criterion of Lorenz dominance holds in every pairwise comparison of a state and a central scheme.[15] During 2014–2018, the (central) LPG scheme was the

income during the period 2010–2013 on a set of household characteristics. 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 on the basis of their predicted household income. Similar to Figure 1, the results in Figure A2 show that better-off households received fewer benefits.

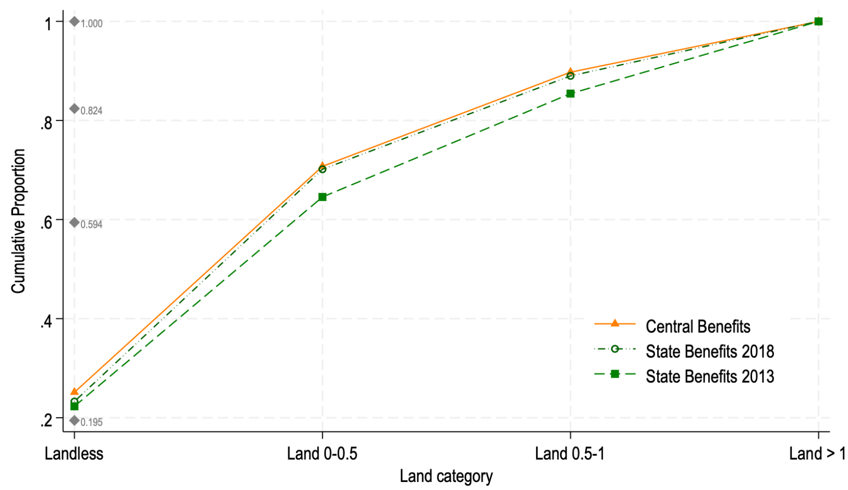
[13] In Figure A3, in the Appendix, we present the implied cumulative benefit shares for households below a specified income quartile, separately for central and state benefits. These are consistent with the patterns in Figure 2, Panel A.

[14] Table A3, in the Appendix, presents the corresponding likelihood of receiving benefits by predicted income quantile (q) and the cumulative proportion of benefits accruing by income quantile. The results are comparable to those presented in Table 3.

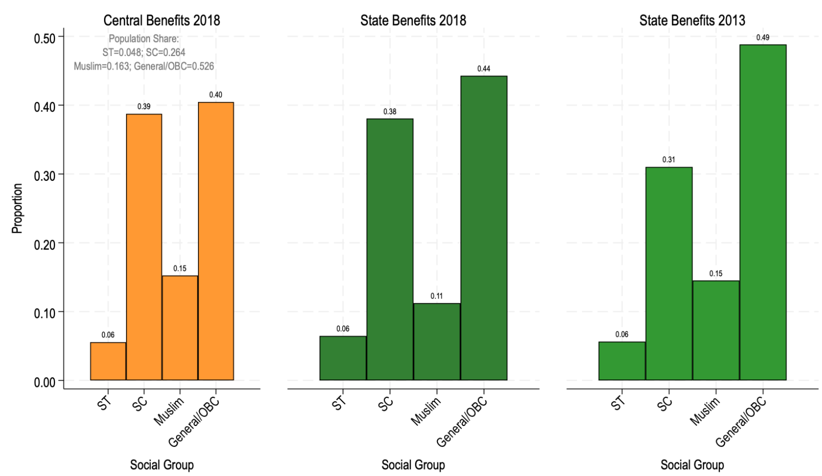
[15] The single exception arises when we compare NREGS with the in-house toilet scheme during 2014–2018: the landless had a larger share in NREGS (26.5% vs 21.4% for toilets), but those with less than 0.5

Figure 2: Targeting of State and Central Benefits.

Panel A: Cumulative Proportion of Benefits Accruing by Land category



Panel B: Proportion of Benefits Accruing by Social group



Notes: Panel A presents the implied (cumulative) benefit shares of households owning below the specified cultivable landholding size, 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 number of benefits received 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 to obtain the cumulative benefit shares. Panel B presents corresponding benefit shares of different social groups: for group g it is $\frac{\omega_g \gamma_g}{\sum_g \omega_g \gamma_g}$ where γ_g is the number of (state or central) benefits accruing to households in g and ω_g is the proportion of sample households in social group g.

Table 3: Targeting of State and Central Benefits. Likelihood of Receiving Benefits and Cumulative Proportion of Benefits Accruing by Land category

	Central Benefits 2014–2018		**State Benefits 2014–2018**		**State Benefits 2010–2013**		**Cumulative Population Share**
	In-House Toilet	LPG Subsidy	NREGS Employment	BPL Card	NREGS Employment	BPL Card	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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	0.195
Landholding Up to 0.5 acres	0.723	0.810	0.710	0.795	0.622	0.843	0.400
Landholding Up to 1.0 acres	0.909	0.956	0.904	0.944	0.845	0.969	0.230

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: $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$.

most progressive: only 4.4% of the benefits accrue to households that owned more than 1 acre of land. The (state) BPL card scheme was less progressive, followed by the (state) NREGS workfare program, and then the (central) in-house toilet program. Since pairwise rankings of central and state programs vary with the specific pair chosen, it is not possible to order central state programs unambiguously with respect to progressivity. Also, not all state programs changed in the same way after 2014: the BPL program became less progressive while the NREGS scheme became more progressive.

Finally, in Table 4, we examine the shares for the different household social groups (SC, ST, Non Hindu, and Other households, that include general caste and OBC households). The terms in the square brackets present the weighted proportion of benefits accruing to households in each social group. During 2014–2018, STs received very similar shares in all four schemes. The SCs had the highest share in the LPG subsidy scheme, and their share

acres had a slightly smaller share in NREGS (71% vs 72.3%). The same is true for households with less than 1 acre of land (90.4% vs 90.9%). The latter two differences are quantitatively negligible compared to the difference for the landless group. If differences for poorer groups are given at least as much weight as for less-poor groups, it seems NREGS was more progressive overall.

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

	Central Benefits 2014–2018		State Benefits 2014–2018		State Benefits 2010–2013		Share of Population
	In-House Toilet	LPG Subsidy	NREGS Employment	BPL Card	NREGS Employment	BPL Card	
	(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]	
Muslim 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 in social group g receiving each benefit provided. The terms in the square brackets present the weighted proportion of benefits accruing to household in social group g and is given by $\frac{\omega_g \gamma_g}{\sum_g \omega_g \gamma_g}$ where γ_g is the raw proportion of benefits accruing to households in social group g and ω_g is the proportion of sample households in social group g (column 7).

became incrementally smaller moving through BPL cards, in-house toilets and NREGS, in that order. Within state programs, the shares held by SCs and STs in the BPL scheme decreased after 2014, while their shares in the NREGS scheme improved. 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.[16]

In summary, the data do not support the claims that the new central welfare programs are more progressive and more programmatic (and therefore better targeted) than pre-existing schemes. As discussed, this is likely because the eligibility and transfer mechanisms for these schemes continued to be defined on the basis of household indicators that local government leaders could use at their discretion.

5 Political Context and Vote Shares

Regardless of whether they were better targeted or not, central welfare programs may have helped improve the BJP's vote share (for example, as a consequence of its aggressive campaign claiming credit for these programs). In the rest of the paper we examine whether receiving these central benefits made our sample households in West Bengal more likely to vote for the BJP, and whether that effect was large enough to explain the dramatic increase

[16]Figure A4 in the Appendix presents the corresponding proportions for a broader set of central and state benefits by land category (Panel A) social group (Panel B) and income quantile (Panel C).

in the BJP's vote share in West Bengal in 2019. However, the central welfare programs cannot be studied in isolation, since the TMC-led state government also ran its own welfare programs and those also likely affected households' choice of political party to support. To better place this analysis in context, below we start by describing the political background in West Bengal over the last 40 years. We then explain the nature of the survey data that we use, before explaining how we attempt to estimate the causal effect of benefit receipts on households' voting choices.

5.1 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 led a breakaway faction to form the *Trinamul* (grass roots) Congress (henceforth, TMC). The TMC frequently entered into 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, and the TMC came to power. The TMC went on to win a majority in 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 A5 in the Appendix). The TMC therefore was the state incumbent both in the 2014 and the 2019 parliamentary elections.

The Bharatiya Janata Party (BJP) was a minor player in West Bengal politics until 2014. During the 2009 national elections, it received 6% of the vote share and won only one of the 42 parliamentary seats in the state (see Figure A5). In the 2014 parliamentary elections, its vote share increased to 17% and it won two seats. The striking change occurred in the 2019 parliamentary elections, when its vote share increased 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 decreased slightly 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.[17]

[17] Figure A6 in the Appendix shows how voter support for the TMC, BJP and the Left Front changed

However, when we compare all three election years, we see that this movement appears to have taken place in two steps: support shifted from the Left Front to the TMC in 2014, and then from the TMC to BJP in 2019. The longitudinal household data we discuss below, however, 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 where the BJP's vote share was increasing across India. However the vote share increase is more dramatic in West Bengal because it started from a lower base. In 2009 the BJP's vote share was around 20% in the country as a whole, but was 10% in West Bengal. 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 dramatic (see Figure A5).

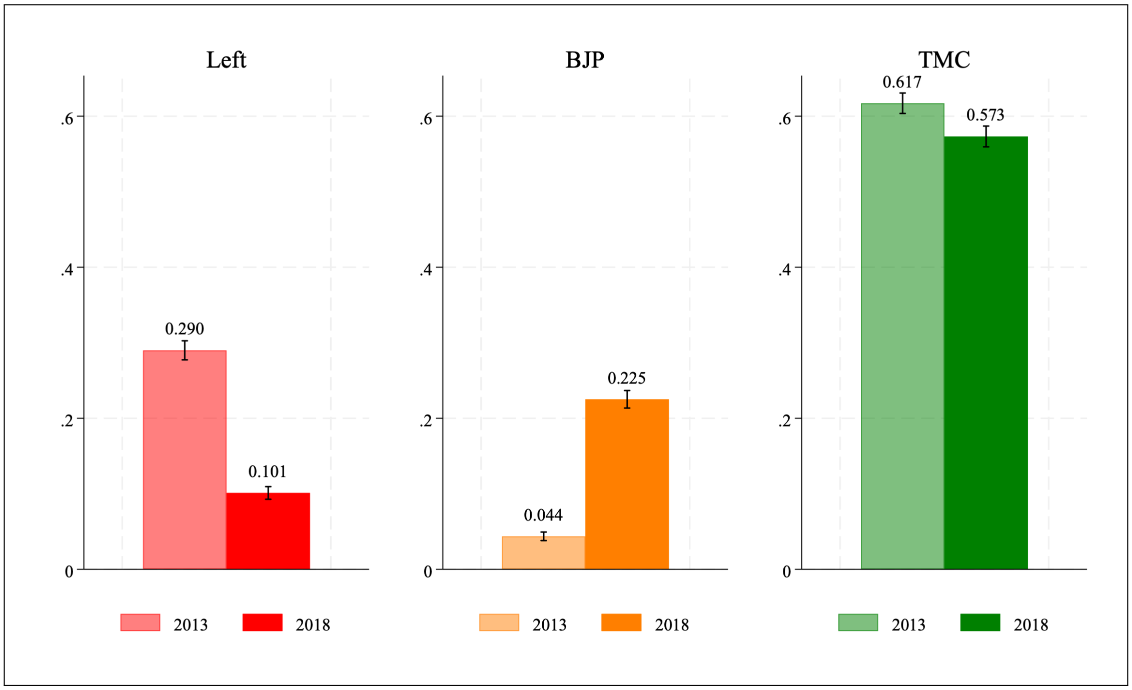
5.1.1 Vote Shares: Survey Data

Our household-level data on support for the different political parties come from straw polls where survey respondents cast a simulated "secret ballot" for the political party they supported.[18] Figure 3 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 also see in our sample 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

over the period 2009 to 2019 across the map of parliamentary constitutences. It is clear that the BJP's large vote shares in 2019 are concentrated in the areas where the Left Front was dominant in 2009. Many political commentators have referred to this change as *Baam theke Ram* ([movement] from the Left to Ram, the Hindu God).

[18] 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 those selected the *None of the Above* option. However, refusal to participate in 2018 was uncorrelated with the party they voted for in 2013.

Figure 3: Poll Vote Shares. Survey Data

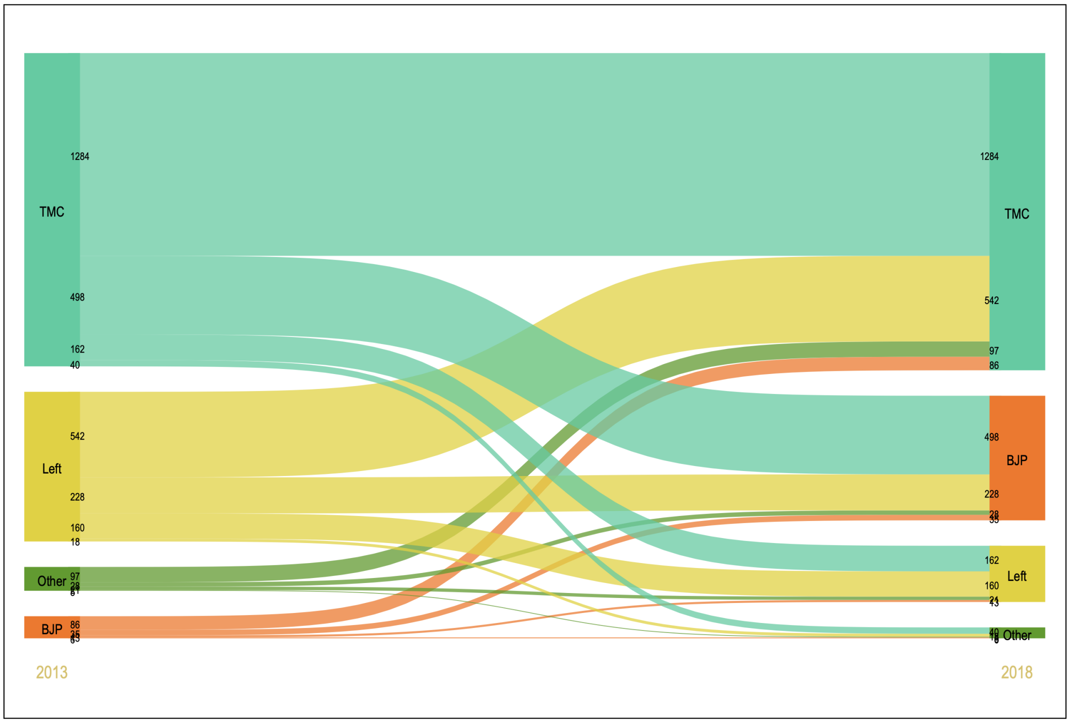


Notes: Proportion of Households voting for Left, BJP and TMC in straw poll conducted in 2013 and 2018 and 90% confidence interval presented.

increase in the BJP's vote share in our survey data is similar to, although weaker 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%). These comparisons are represented visually in Figure A7 in the Appendix. Although the magnitudes of change differ, the survey data indicate the same qualitative changes we saw 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' support for political parties may only have crystallised later. In Section 6.1.2 we also consider the possibility that some "shy" BJP supporters may have chosen not to participate in the straw poll in 2018.

The longitudinal nature of our dataset allows us to look beyond the cross-sectional patterns and examine how individual voters' political leanings changed between 2013 and 2018. As we see in the Sankey diagram in Figure 4, the increase in the BJP's vote share was not caused simply by a movement of Left Front supporters toward the BJP. In fact, a large number of households that voted for TMC in 2013 switched to the BJP in 2018, while

Figure 4: Vote Switching Patterns. Survey Data



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

at the same time, an even larger number of 2013 Left Front voters switched to TMC. This indicates that rather than a simple swing of support from a left-wing to a right-wing political party, the changing voting patterns reflect a broader churning.

6 Estimating Effects of Benefits on Voting Patterns

We draw upon the Bardhan et al. (2024) model of two party competition, where higher level governments allocate budgets for different welfare programs across different local governments, who in turn allocate their assigned budgets across local citizens. Citizens vote in periodic elections, on the assumptions that if they win, local incumbents will continue to supply the most recent benefit allocations, and that if the challengers win, they will allocate benefits as per their stated policy platform. In a programmatic welfare system incumbents deliver benefits unconditionally; in a clientelistic system they monitor how citizens vote and deliver benefits to citizens who voted for them in the previous election. Citizens' choices of party to support depends on the utility of anticipated benefits and the attribution of credit to incumbents at various levels of government, as well as on citizen and party characteristics such as ideology, identity, loyalty, exposure to campaign advertisements, and other idiosyncratic shocks. This generates the following equation predicting how votes will respond to the current distribution of benefits:

$$\text{Vote Party}_{ipt} = \beta_{0pt} + \beta_{spt}\text{State Benefits}_{it} + \beta_{cpt}\text{Central Benefits}_{it} + \gamma_{pt}\mathbf{X}_i + \varepsilon_{ipt} \tag{1}$$
$$\text{for } t = \{2013, 2018\}; \text{and } p = \{\text{TMC, BJP, Left}\}$$

where 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, which affect party-specific preferences. State Benefits$_{it}$ and Central Benefits$_{it}$ denote state and central benefits that household i received between years $t-1$ and t.[19] The coefficients β_{spt} and β_{cpt} represent the effect of receiving state and central benefits on citizens' votes for each party in each period. By allowing them to vary across election year t, we allow for possible changes in voters' belief that the incumbent will be re-elected, and changes in how they credit different parties for the welfare programs. Similarly, the coefficients γ_{pt} may vary across election year t if voters' preferences for different parties change.

The regression specification (1) is subject to omitted variable bias, since unobserved household characteristics affecting voting patterns which are included in the error term could be correlated with benefits received. If local officials targeted benefits to "loyal" voters, this would bias our estimates to find that benefits have larger effects on the likelihood that a household votes for the incumbent. If instead officials targeted "swing" voters, the bias could go in either direction, depending on how effective benefits are at inducing households to switch their support to the incumbent. The incumbent party's incentives to deliver benefits to different voters may also depend on how competitive they perceive the next election to be. Less secure incumbents may deliver more benefits to swing (rather than loyal) areas, which could bias the estimates downward.

If these unobserved household characteristics ('loyal' versus 'swing') do not change over time, we can address this problem under the assumption of non-time-varying regression coefficients ($\beta_{0pt} = \beta_{0p}; \beta_{spt} = \beta_{sp}; \beta_{cpt} = \beta_{cp};$ and $\gamma_{pt} = \gamma_p,$ for all t) by estimating a first difference version of equation (1) which removes the effect of these unobserved

[19]For the 2013 round, central benefits are set equal to zero, since those programs had not come into existence at that time.

characteristics:

$$\Delta\text{Vote Party}_{ip} = \beta_{sp}\Delta\text{State Benefits}_i + \beta_{cp}\Delta\text{Central Benefits}_i + \Delta\varepsilon_{ip} \tag{2}$$

However, the assumption that $\gamma_{pt} = \gamma_p$ is restrictive. It amounts to assuming that different socio-economic groups undergo similar changes in their ideological party preferences (i.e., unrelated to utility from benefits received). We can relax this assumption if we run the following augmented version of equation (2), where ξ_p denotes $\Delta\gamma_{pt}$, the change in ideological party preferences between the two years of socio-economic group defined by household characteristics X_i:

$$\Delta\text{Vote Party}_{ip} = \beta_{sp}\Delta\text{State Benefits}_i + \beta_{cp}\Delta\text{Central Benefits}_i + \xi_p\mathbf{X}_i + \Delta\varepsilon_{ip} \tag{3}$$

Equation (3) is based, however, on a linearity assumption which requires equally-sized changes in benefits in either direction to have equal and opposite effects on how citizens vote. This assumption may fail to hold, e.g., if a household receives one fewer benefit than before the negative effect on the likelihood that they vote for the local incumbent may be larger than the positive effect of receiving one more benefit. To allow for this possibility, we can modify equation (3) to estimate separate regressions for the likelihood that household i switched towards party p (voted for party p' in 2013 and for party p in 2018), and away from party p (voted for p in 2013 and p' in 2018).

We start in Panel A of Table 5 by presenting results of the first difference regressions (2) and (3) (columns 1–3 and 4–6 respectively). For each household we aggregate the number of state and central benefits respectively across different programs, and then compute the change in these aggregates between the periods 2010–2013 and 2014–2018.

Irrespective of whether or not we control for household characteristics, the first difference regressions are qualitatively and quantitatively similar. These results show that the receipt of an additional state benefit raised the likelihood that the household head voted for the TMC by 3.2–3.6 percentage points, and reduced the likelihood of voting for the BJP by 1.2–2.6 percentage points. The effect of an additional central benefit is not statistically significant, but the point estimates suggest an increase in the likelihood that the household head voted for the BJP by upto 2.7 percentage points.

Welfare benefits may change voting patterns differently in different directions. In Panel B of Table 5, we separately estimate the effect of an additional benefit received on the

Table 5: Change and Switch in Voting Behaviour

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	**First Difference Regression**			**Augmented First Difference Regression**		
	TMC	BJP	Left	TMC	BJP	Left
Change in Central Benefits	0.032	0.005	-0.013	0.005	0.027	-0.003
	(0.022)	(0.018)	(0.016)	(0.021)	(0.016)	(0.016)
Change in State Benefits	0.032***	-0.012	-0.025**	0.036***	-0.026***	-0.016*
	(0.012)	(0.008)	(0.010)	(0.012)	(0.008)	(0.009)
Number of Households	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.009	0.002	0.007	0.029	0.057	0.023
Equality of Effects†	-0.000458	0.0170	0.0119	-0.0311	0.0523***	0.0130
	(0.0294)	(0.0197)	(0.0218)	(0.0274)	(0.0179)	(0.0206)
Panel B: Switch in Voting	**Against TMC**	**To TMC**	**To BJP**	**Against Left**		
Change in Central Benefits	-0.011	-0.006	0.016	0.004		
	(0.014)	(0.012)	(0.015)	(0.014)		
Change in State Benefits	-0.019***	0.017**	-0.026***	0.010		
	(0.007)	(0.008)	(0.007)	(0.008)		
Number of Households	3,500	3,500	3,500	3,500		
R-squared	0.022	0.020	0.055	0.027		
Equality of Effects†	0.00819	-0.0229	0.0425**	-0.00529		
	(0.0173)	(0.0160)	(0.0168)	(0.0177)		

Notes: OLS regression results reported. Columns 1–3 of Panel A reports the results of the regression specification given by equation (2), while columns 4–6 reports the results of the regression specification given by equation (3). The dependent variables indicate a change in political support for a particular party between 2013 and 2018. In columns 4–6, regressions control for religion, caste and the migration status of household, gender, marital status, education and occupation of the household head, household size and indicator for residence in Hugli district. Panel B reports results from a variation of the regression specification given by equation (3) where the dependent variable is either the likelihood that i switched towards party p (voted for p in 2018 and some other party p' in 2013), or away from party p (voted for p in 2013 and some other party p' in 2018). 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 indicator for residence in Hugli district. † : Test for equality of effects of change in Central and State Benefits received on change in vote for relevant party. Standard errors in parentheses are clustered at the village level. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

likelihood that a voter switches away from, or toward the TMC (in columns 1-2), switches toward the BJP (column 3) and switches away from the Left (column 4).[20] All reported regressions are run on the full dataset of 3500 households. An additional state benefit received reduces the likelihood that a household switched their political support away from TMC by a statistically significant 1.9 percentage points, and toward the BJP by a statistically significant 2.6 percentage points; it increased the likelihood of switching to the TMC by 1.7 percentage points. In contrast, central benefits have no statistically significant effects.

However, the specifications shown in Table 5 are based on the assumption that voters' responses to benefits, estimated by β_{sp} and β_{cp}, do not change over time. This rules out the possibility that patterns of incumbency at the central government, and credit claiming by the BJP after 2014 changed voters' responsiveness to benefits. To test this assumption, we can separately estimate the two cross-sectional regressions given by equation (1) for the two rounds. OLS versions of these cross-sectional regressions are however subject to concerns for omitted variable bias, as explained above. To address this concern, we note that in Bardhan et al. (2024)'s model, as in standard political economy models of redistributive politics (Grossman and Helpman, 1996, Dixit and Londregan, 1996), two-party competition leads to an intra-village allocation that maximizes a political-welfare-weighted utilitarian welfare function, where the political welfare weight of any socio-economic group depends on the relative importance it assigns to welfare benefits relative to its preferences for the different parties (its "swing" propensity), and the marginal utility it derives from the benefit. This generates predictions for the vote shares of the two parties as a function of allocated budgets and local incumbency patterns.

Anticipating these consequences for vote shares, incumbents in the district government allocate benefits across local governments in their jurisdiction so as to maximize an objective function that depends on their likelihood of winning the next election, less a cost that is proportional to the resulting inter-village variance of allocated budgets, reflecting the costs of dealing with complaints of unfair treatment from subjects, media watchdogs or auditors. Bardhan et al. (2024) show that this model generates predictions for how benefits are allocated across different villages in any given year as follows. From a given welfare program with total (per capita) district budget B, village v receives a budgetary assignment B_v given

[20] Since very few voters (4.43%) voted for the BJP in 2013 and very few voters (10.11%) voted for the Left in 2018, we do not estimate regressions corresponding to a switch away from the BJP or a switch toward the Left.

by

$$B_v = B + T_v - \sum_{v'} n_{v'} T_{v'} \tag{4}$$

where T_v is a parameter representing the "marginal political deservingness" of village v and n_v is the population weight of village v. The parameter T_v depends on the alignment between parties controlling the district and local government in village v, the voting propensities of its residents and how competitive the next election is expected to be. This parameter, and hence B_v, is therefore likely to be correlated with village characteristics that affect how vote shares in the village respond to benefits. This potentially biases the estimates of the OLS regression of votes on benefits received in equation (1) .

Bardhan et al. (2024) provide a way of correcting for this bias. Equation (4) can be written as

$$B_v = B + (1 - n_v)T_v - \sum_{v' \neq v} n_{v'} T_{v'} \tag{5}$$

Consider n'_v, the population weight of village v'. Observe that if $n_{v'}$ is close to zero, then the cross-effect of $T_{v'}$ on $B_v; v \neq v'$ will be negligibly small. Conversely, the benefit $B_{v'}$ allocated to any other village v' is asymptotically independent of T_v if the number of villages in the district becomes large enough. It follows that the average benefit allocated to all other villages v' "almost" satisfies the required exclusion condition for an instrument for B_v, under the assumption that, conditional on district fixed effects, the $T_{v'}$s are independent across villages. Therefore, under this assumption the average allocation B_{-v} to all villages other than v is a valid instrument for B_v if the number of villages in a district is large enough. Moreover, given a fixed budget B for the district, we expect this instrument to have a negative impact on B_v: the more deserving the other villages are, they receive more benefits thus leaving less for v.

To obtain an instrument for household (rather than village) level benefit allocations, we interact the predicted village budget with pre-determined household socio-economic characteristics. 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 ($\bar{B}_{-v,dt}$), and fixed household characteristics (H_{ivd}), such as caste, landownership, education, and religion, which are significant determinants of whether a household receives benefits (in the intra-village allocation):

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

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. In addition, we include district fixed effects in the regression, to control for unobserved heterogeneity across districts.[21]

Turning to Table 6, we present both the OLS and IV regression results for 2013 in Panel B, and for 2018 in Panel A.[22] In both years, the IV estimates are larger in magnitude than the OLS coefficients, indicating that the OLS estimates are biased towards 0. In 2018, state benefits raised the likelihood of voting for the TMC by 6.0/8.9 percentage points, mainly at the expense a reduction in the likelihood of voting for the BJP by 4.6/8.5 percentage points. These coefficients are precisely estimated and statistically significant with p-value < 0.01. The effects of state benefits on the propensity that a household voted for TMC is significantly greater than the corresponding probability that it voted for BJP: the 95% confidence intervals do not overlap for either the OLS or the IV regressions. This provides evidence in favour of Hypothesis P1(b). The effects of central benefits are not precisely estimated, with one exception: the OLS estimate suggests that central benefits increase the probability that a household votes for the BJP by 2.7 percentage points (statistically significant at 10%). The corresponding IV estimate is 6.4 percentage points, but is not statistically significant at any conventional level of significance. The IV estimates show that the increased likelihood of voting for the BJP came at the expense of a 2.6 percentage point reduction in the vote share of the TMC and a 2.2 percentage point reduction in the vote share of the Left front, but these cross-effects are not statistically significant. As a result, we do not have enough power to test whether central benefits affected the vote shares of the BJP and TMC differently. Hence Hypothesis P1(a) cannot be validated using our data. However, we do find evidence that the effects of state and central benefits are different – we can reject the null hypothesis that they both had the same effect on the likelihood that the household voted for the TMC (p-value = 0.07, column 2), as well as the BJP (p-value = 0.01, column 4). This implies that Hypothesis P1(c) is validated by our data.

[21] A similar approach has been adopted in many developing country contexts such as Lamichhane and Mangyo (2011), Bai et al. (2019), Dang and La (2019), Sedai et al. (2020), Maitra et al. (2023). As argued by Levitt and Snyder Jr (1997) and Bardhan et al. (2024), criticisms of this approach in settings with peer effects (Betz et al., 2018, McKenzie, 2021) do not apply to our setting where budgetary assignments are determined hierarchically in the presence of strategic considerations. Of course, the standard disclaimer for IV estimates applies in the presence of heterogeneous treatment effects: the 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.

[22] The first stage results for the IV regressions are presented in Table B1 in the Appendix.

Table 6: Voting Patterns in 2018 and 2013. The Effect of Aggregate State and Central Benefits

	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Panel A: Voting for Party in 2018	**TMC**		**BJP**		**Left**	
Central Benefits 2014–2018	0.006	-0.026	0.027*	0.064	-0.005	-0.022
	(0.019)	(0.056)	(0.016)	(0.048)	(0.009)	(0.032)
State Benefits 2014–2018	0.060***	0.089***	-0.046***	-0.085***	-0.009*	-0.010
	(0.010)	(0.022)	(0.009)	(0.019)	(0.005)	(0.010)
Number of Households	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.050		0.063		0.022	
Equality of Effects†	-0.0533**	-0.114*	0.0738***	0.149***	0.00362	-0.0120
	(0.0244)	(0.0641)	(0.0191)	(0.0538)	(0.0116)	(0.0367)
First Stage F-statistics						
Central Benefits		85.49		85.49		85.49
		[0.000]		[0.000]		[0.000]
State Benefits		67.33		67.33		67.33
		[0.000]		[0.000]		[0.000]
Anderson-Rubin ($\chi^2(28)$)		83.26		98.67		38.82
		[0.000]		[0.000]		[0.000]
Panel B: Voting for Party in 2013	**TMC**		**BJP**		**Left**	
State Benefits 2010–2013	0.032**	0.054	0.002	0.017	-0.043***	-0.086**
	(0.012)	(0.039)	(0.003)	(0.011)	(0.012)	(0.036)
Number of Households	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.039		0.028		0.046	
First Stage F-statistics						
State Benefits		175.94		175.94		175.94
		[0.000]		[0.000]		[0.000]
Anderson-Rubin ($\chi^2(15)$)		121.51		78.38		403.80
		[0.000]		[0.000]		[0.000]

Notes: Year specific OLS regression results presente. 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. † : Test for equality of effects of Central and State Benefits received on voting for relevant party. 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.

Panel B, which tests Hypothesis P2, shows that if a household received one extra state benefit between 2010 and 2013, the likelihood that it voted for the TMC increased by 3.2/5.4 percentage points (columns 1 and 2). Hypothesis P2(a) is thus validated. These effects are significantly smaller than those in Panel A: the 90% confidence intervals do not overlap. Hypothesis P2(b) is also supported. In contrast to the strong negative effects seen in Panel A, we estimate a small positive effect on likelihood that the household voted for the BJP The greater likelihood of voting for the TMC came at the expense of a statistically significant 3.4/9.2 reduction (columns 5 and 6) in the likelihood of voting for the Left Front (both estimates had $p < 0.01$). This reflects the fact that in 2013, the political contest was largely between the long-established Left Front and the challenger TMC, whereas by 2018 it had changed to a contest between the TMC and the BJP. Consequently the effects of state benefits on the BJP and Left Front's vote shares were also significantly different between the two survey rounds: the 90% confidence intervals do not overlap. This provides decisive evidence against hypothesis P2(c) which states that clientelism declined in West Bengal over this period. State benefits actually became more effective at generating votes for the TMC after 2014. This also leads us to reject the validity of the fixed effects regression specification, which assumes that benefits have the same effect on the likelihood that a household votes for a particular party in both years.[23]

We now examine what these estimates imply for the validity of Hypothesis P3, which states that changes in welfare programs explain the increase in the BJP's vote share since 2014. As we see in Table 7, the scale of state benefits increased from 1.2 to 1.8 benefits per household between 2010–2013 and 2014–2018. At the same time, state benefits became more effective at generating votes for the TMC – an additional benefit received by the household increased the likelihood that a household voted for the TMC increased from 5.4 to 8.9 percentage points. The product of the two implies that state benefits should have increased the TMC's vote share by 9.7 percentage points. This is partly offset by the negative effect of the increased coverage of central benefits, which is predicted to have lowered the TMC's vote share by 1.4 percentage points. We end up with a net predicted increase in the TMC's vote share of 8.3 percentage points. In contrast, the TMC's vote share actually *decreased* by 4.4 percentage points.

The corresponding prediction for the BJP is that its vote share should have declined by 13.7 percentage points. This was driven by the expansion of state benefits and the negative

[23] In Table A4 in the Appendix, we present the IV version regressions presented in Table 5. Change in Central and State Benefits instrumented by the difference version of the leave-one-out instrument. The IV estimates are larger, indicating the OLS estimates are biased downwards.

predicted effect this had on the probability that a household voted for the BJP in 2018 (17.2 percentage points), as the BJP became the TMC's principal competitor. This large negative effect was only mildly counterbalanced by a 3.5 percentage points increase in the BJP's vote share caused by the introduction of central benefits. The previous literature (Deshpande et al., 2019) and media accounts have focused on the expansion in central benefits, but have not accounted for the growth in the overall scale of state benefits, and their greater effectiveness at moving votes away from the BJP to the TMC. Thus, contrary to other accounts, our analysis suggests clientelistic welfare programs have both grown in scale, and become more effective at generating votes in West Bengal. Hypothesis P3 is clearly rejected by our data.

Table 7: Predicted Effect of Aggregate State and Central Benefits on Votes

	Mean	**Unit Effect**		**Total Effect**	
	(Q^t)	$(\hat{\beta}^t_{TMC})$	$(\hat{\beta}^t_{BJP})$	$(Q \times \hat{\beta}^t_{TMC})$	$(Q \times \hat{\beta}^t_{BJP})$
	(1)	(2)	(3)	(4)	(5)
Central Benefits 2014–2018	0.54	-0.026	0.064	-0.014	0.035
State Benefits 2014–2018	1.79	0.089	-0.085	0.159	-0.152
State Benefits 2010–2013	1.16	0.054	0.017	0.063	0.020
Predicted Effect on Change in Vote Share					
Central Benefits				-0.014	0.035
State Benefits				0.097	-0.172
Total Predicted Effect of Benefits (Central + State)				0.083	-0.137
Actual Change				-0.044	0.181

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 3. 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.

6.1 Robustness Checks

We now discuss the robustness of these results to alternative specifications of the regression specification in equation (1).

6.1.1 Interactions of Voting patterns with Local Incumbency

So far we have assumed that households respond to an increase in state welfare benefits by rewarding the party in charge of the state government. However since local village councils play an important role in benefit delivery, it is possible that voters instead rewarded the political party that controlled the village council government (*gram panchayat* or GP). To incorporate this source of heterogeneity, we add an interaction between benefits received and an indicator for the party that had the most seats in the GP. The corresponding OLS regression results are presented in Table A5 in the Appendix. The estimates indicate that in 2018, an additional state benefit received in the jurisdiction of 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 4.9 percentage point decline in the likelihood that they voted for BJP. In contrast, in a GP controlled by the Left Front, the state benefit increased the TMC's vote share by a weaker and statistically not significant 3.2 percentage points, and decreased the BJP's vote share by a statistically significant 2.4 percentage points. We see similar patterns in 2013: in GP not controlled by the Left Front, an additional state benefit increased the TMC's vote share by 10.3 percentage points and decreased the Left Front's vote share by 9.6 percentage points, whereas in GP controlled by the Left Front, state benefits were significantly less likely to translate into votes for TMC (point estimate = 2.2 percentage points, not statistically significant).

6.1.2 Shy BJP Voters?

Recall that while all households participated in the straw poll in 2013, 8.1% of households did not participate in 2018. One explanation for this non-participation could be that these households supported the BJP but were hestitant to reveal this in a straw poll. 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 cast the straw poll ballot for the TMC in 2013, and 6.9% refusal rate of those who cast the ballot for the Left Front in 2013. Nevertheless, as a robustness exercise, we re-categorize these refusals as shy BJP voters, and re-estimate the regression corresponding to equation (1). The resulting estimates (presented in Table A6 in the Appendix) are qualitatively similar to those presented in columns 3 and 4 of Table 6: the IV estimates presented in column 2 of Table A6 imply that an additional state benefit received in the period 2014–

2018 reduces the likelihood that the household votes for the BJP by 7.6 percentage points, as against the previously estimated 8.5 percentage point reduction. An additional central benefit received during the same period increases the likelihood that the household votes for the BJP by a non-significant 3.9 percentage points, as against the previously estimated 6.6 percentage points.

6.1.3 Allowing Individual Welfare Benefits to Have Different Effects

Another potential concern with our preceding results is that the aggregate benefits variables are simple counts of the state and central receipts that households received, valuing all schemes equally and assuming that citizens rewarded political parties the same extent for each. We now allow different programs to have heterogenous impacts on voting propensities. In Table A7, in the Appendix, 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.[24] 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 Table A7, 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 effect in 2018: receiving this benefit raised the likelihood that a household voted for the TMC by 22.7 percentage points and lowered the likelihood that it voted for the BJP by 20.4 percentage points. Neither of the two central benefits has a statistically significant effect, and surprisingly, the receipt of the LPG subsidy has a negative, although statistically insignificant, effect in column 4. Once again, contrary to the hypothesis of declining clientelistism, NREGS benefits in fact boosted the TMC's vote share in 2018 by a larger 22.7 percentage points than the 2013 effect of 14.4 percentage points, although the two point estimates are not significantly different from each other. Moreover they reduced the BJP's vote share only in 2018; in 2013 they had a positive effect. Hence the NREGS had a stronger negative effect on the BJP's vote share after 2014.[25]

[24]We continue to assume that BPL cards are state benefits, for the reasons mentioned earlier in the Introduction: they were introduced before 2014, and local governments continue to be in charge of selecting BPL recipients. So it is plausible that BPL recipients believe the TMC is responsible for these cards. This is consistent with what we see in Table A7: we estimate a positive point estimate of BPL benefits on the TMC's vote share, and a negative point estimate on the BJP's vote share.

[25]Table A9 in the Appendix shows these results continue to hold when we include additional Central and State Benefits (zero-balance *Jan Dhan* bank accounts, farmer credit cards, drinking water (from the GP) and community toilets (from the GP)). We estimate positive point estimates for the effect on the

Table A8, in the Appendix, computes the resulting implied effect on predicted vote shares. Welfare benefits (Central + State) contributed to a 6.1 percentage point increase in the vote share of the TMC and a 16.3 percentage point drop in the vote share of the BJP. Thus we continue to find that welfare programs cannot explain the observed changes in the vote shares of the TMC and the BJP.[26]

6.1.4 Heterogeneous Voting Impacts across Different Land Categories

Different socio-economic groups may also respond to benefits differently. In Table A11 we present OLS estimates of the impacts of aggregate state and central benefits respectively, from regressions run separately for four land categories, using the same specification as in equation (1). In no landholding category is an increase in central benefits associated with a statistically significant change in the likelihood of voting for either party. In contrast, an additional state benefit caused increased the likelihood that a household voted for the TMC by similar amounts in different landholding categories: the effect decreased only gradually from 6.8 among the landless to 4.5 percentage points in the to higher landholding categories, and similarly decreased the likelihood that it voted for the BJP in 2018 by similar extents, from 5.3 to 3.4 percentage points. These effects are stronger in 2018 than in 2013. As we see in Table A12 in the Appendix, this implies an increase of 6.1 percentage points in the TMC's vote shaare and a decrease of 6.8 percentage points in the BJP's vote share.[27]

TMC's vote share and negative point estimates for the effect on the BJP's, although not all estimates are statistically significant. The central government's toilet scheme raised the BJP's vote share by a statistically significant 7.3 percentage points.

[26]Even with the extended set of benefits, we see that central and state welfare benefits contributed to a 1 percentage point increase in TMC vote share and a 5.2 percentage point drop in BJP vote share. See Table A10 in the Appendix.

[27]Finally, Table A13 in the Appendix, presents the corresponding OLS estimates from regressions run separately for the four different income quartiles. The effects of central benefits are mixed, ranging from an increased likelihood of voting for the BJP for the lowest income quartile, to a positive effect on the likelihood of voting for the TMC in the highest-income quartile. In contrast, households in every quartile responded to state benefits in 2018 by roughly the same extent; the differences are not statistically significant across quartiles. Note also that voters in all groups were markedly more responsive to state benefits in 2018 than in 2013. In Table A14 in the Appendix we see once again, that the results predict an increase in the TMC's vote share by 7 percentage points, and a decrease in the BJP's vote share by 6.8 percentage points.

7 Explaining the Actual Post-2014 Rise in BJP Vote Share

If welfare benefits do not explain the rise in the BJP's vote share after 2014, what other factors might be responsible instead? In this Section we consider several alternative hypotheses.

7.1 The Role of Changes in Household Economic Circumstances

A large and growing literature mainly focused on Western countries has argued that voters' growing support for populist and right-wing nationalist parties is a response to the economic insecurity and distress resulting from globalization, trade shocks or immigration (see, for example, Colantone and Stanig, 2018, 2019, Autor et al., 2020, Oliveira, 2022). To examine whether similar factors can explain our findings, we now check whether our results change if we control for changes in economic circumstances between 2013 and 2018.

Our measure of household economic circumstances is based on households' farm incomes – specifically, value-added (defined as sales revenues less the cost of purchased inputs) from the cultivation of potatoes since they are the most profitable crop in our study region. We use the voting regression specification for 2018 from equation (1), and augment the set of regressors to include change in potato value-added (in Rs. '0000). Specification 1 (Columns 1–4) of 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 central and state benefits are unaffected even after we include this control. Moreover, the estimated coefficients on change in potato value added are not quantitatively or statistically significant. Thus we do not find evidence that change in economic circumstances directly affected voting patterns in 2018.

We can also account for the endogeneity of change in potato value-added using a shift-share type instrument, where we instrument the change in potato value-added with the change in the price of potatoes between 2013 and 2018 interacted with the acreage under potato cultivation in 2011 at the individual farmer level ($\Delta\Pi^p = (P^p_{2018} - P^p_{2013}) \times \text{Acreage}^p_{2011}$), where P^p_t is the average sales weighted price of potato in year t; $t = 2013, 2018$ for the Kolkata market, obtained from the Agmark dataset. These are market prices, determined by aggregate demand and supply, whereas our sample farmers are small and individually have no ability to influence the Kolkata prices. Acreage^p_{2011} denotes the acreage under potato cultivation in year 2011. The results presented in Specification 2 (columns 5 and 6) of Table 8 show that accounting for the potential endogeneity of change in potato value added does not change our main results.[28]

We also investigate possible interaction effects between changes in a household's economic condition and its receipt of state or central benefits. We instrument for the change in potato value-added, change in potato value-added × Central Benefits and Change in potato value-added × State Benefits using $\Delta\Pi^p$, $\Delta\Pi^p \times$Central Benefits and $\Delta\Pi^p \times$State Benefits, where $\Delta\Pi^p = (P^p_{2018} - P^p_{2013}) \times \text{Acreage}^p_{2011}$. The corresponding regression results are presented in Specification 3 (columns 7–10) of Table 8. The results indicate that the effects of benefits are heterogeneous according to changes in potato incomes experienced. The effect of state benefits on the likelihood of voting for TMC decreases (and correspondingly the likelihood of voting for BJP increases) when households experience an increase in potato value-added. This is consistent with the argument that an increase in income levels is associated with a decline in voter responsiveness to benefits, as predicted by theories of clientelism (Stokes, 2005).

7.2 Violence during the 2018 *Gram Panchayat* Elections

During the 2018 local government elections in West Bengal, the media reported a number of violent incidents around the state, specifically targeted at candidates standing for election. Observers have suggested that the supporters of the TMC initiated this violence so as to intimidate their political opponents into withdrawing their candidacy. They have further argued that voters responded to this by voting against the TMC in the subsequent 2019 parliamentary elections, which in turn contributed to the increase in the BJP's vote share. To examine this hypothesis, in Figure A8 in the Appendix we plot the BJP's 2019 vote share in each parliamentary constituency against the fraction of panchayat elections within that

[28]In the regression results presented in columns 5 and 6, we do not account for the potential endogeneity of central and state benefits received. We also examine the robustness of our results on the effect of changes in economic circumstances on the pattern of voting in 2018 by considering alternative measures of change in economic circumstances: change in employment income, change in large livestock owned, change in land ownership, change in non agricultural income and change in household income. The corresponding OLS regression results are presented in Table A15 in the Appendix. Irrespective of how we measure change in economic circumstances, we see that the coefficients on central and state benefits are unaffected even after we control for the possibility that our previous findings were driven by households that faced changing economic circumstances. Moreover, the estimated coefficients on the measure of change in economic circumstances are quantitatively and statistically insignificant.

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

	Specification 1				Specification 2		Specification 3			
	TMC		BJP		TMC	BJP	TMC		BJP	
	OLS	IV	OLS	IV	IV	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Central Benefits 2014–2018	0.006	-0.026	0.027*	0.064	0.006	0.027*	0.018	-0.021	0.027	0.052**
	(0.019)	(0.057)	(0.016)	(0.048)	(0.019)	(0.016)	(0.021)	(0.024)	(0.018)	(0.021)
State Benefits 2014–2018	0.060***	0.090***	-0.047***	-0.085***	0.060***	-0.047***	0.069***	0.080***	-0.054***	-0.059***
	(0.010)	(0.022)	(0.009)	(0.019)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
Change Potato Value-added	0.029	0.035	-0.008	-0.015	0.025	-0.011	0.090***	0.111**	-0.051	-0.056
	(0.036)	(0.036)	(0.033)	(0.034)	(0.050)	(0.045)	(0.031)	(0.049)	(0.034)	(0.050)
Change Potato Value-added × State Benefits							-0.039*	-0.096***	0.038**	0.060**
							(0.020)	(0.028)	(0.018)	(0.025)
Change Potato Value-added × Central Benefits							-0.057	0.136*	0.003	-0.121*
							(0.046)	(0.076)	(0.052)	(0.065)
Number of Households	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,500
R-squared	0.050		0.063				0.054		0.066	
First Stage										
Central Benefits		84.60		84.60						
		[0.000]		[0.000]						
State Benefits		68.07		68.07						
		[0.000]		[0.000]						
Change Potato Value-added					85.50	85.50		38.52		38.52
					[0.000]	[0.000]		[0.000]		[0.000]
Change Potato Value-added × State Benefits								40.82		40.82
								[0.000]		[0.000]
Change Potato Value-added × Central Benefits								22.49		22.49
								[0.000]		[0.000]

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. Potato Value added is calculated in real terms (using the All India Price Index Number for Agricultural Labourer, General Index, $1986-87=100$) in Rs. ('0000). Change in potato value-added = Potato value-added (2018) – Potato value-added (2010–2013). In columns 2 and 4 we account for the endogeneity of central and state benefits only while in columns 5, 6, 8 and 10 we account for the endogeneity of change in value added only. In columns 2 and 4, the benefits variables are instrumented by the "leave out" instrument described in the text. In columns 5, 6, 8 and 10, we instrument the change in real potato value-added using the following shift-share instrument: $(P^p_{2018} - P^p_{2013}) \times \text{Acreage}^p_{2011}$, where P^p_t are the potato prices for the Kolkata market in year t, $t = 2013, 2018$, obtained from the Agmark dataset. Acreage^p_{2011} denotes the acreage under potato cultivation in year 2011. Standard errors, clustered at the village level in parentheses. Significance: $^{***}p<0.01, ^{**}p<0.05, ^{*}p<0.1$.

constituency, where the TMC candidate ran unopposed in 2018.[29] We find no correlation between the incidence of unopposed TMC candidature and voting patterns in the 2019 election.

7.3 Variation Across Socio-Economic Groups

Finally, we examine variations in vote share changes across social groups defined by ethnicity, religion and immigrant status. We start by examining variations in the raw data on vote shares, and then show vote share regressions, which allow heterogeneity across different social groups while controlling for benefits received.

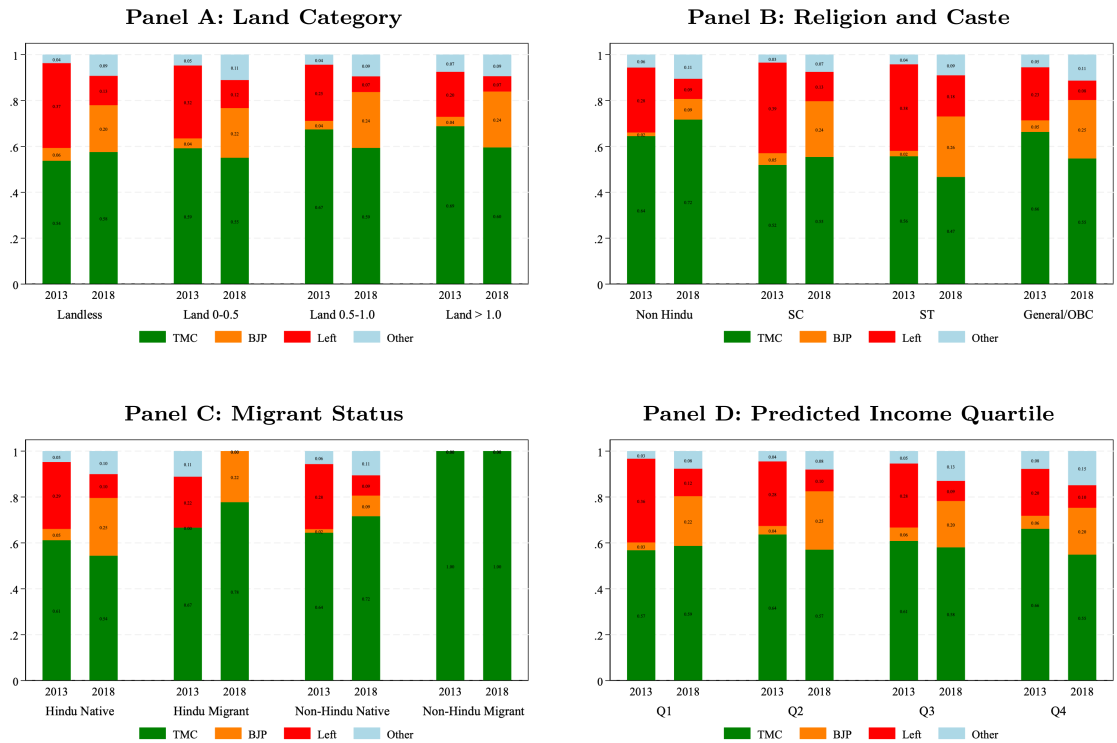
Figure 5 shows how vote shares changed over time in different population sub-groups. In Panel A we see that the BJP's vote share increased by nearly uniform extents across different landowning categories, from 4–6% in 2013 to 20–24% in 2018. A similar pattern appears across different income quartiles in Panel D. Panel B shows that the shift was markedly smaller among non-Hindus (an increase of 7 percentage points), compared to an increase of 20 percentage points among general caste and other backward castes (OBCs), 19 percentage points among scheduled castes (SCs) and 24 percentage points among scheduled tribes (STs). Panel C compares shifts across groups defined by religion and immigration status of the household.[30] Among Hindu natives and Hindu immigrants, the BJP's vote share increased by 20–22 percentage points. However among non-Hindus, the BJP's vote share increased by a substantially smaller 7 percentage points. No non-Hindu immigrant voted for the BJP in either round. Thus, non-Hindus and in particular, non-Hindu immigrants were much less likely to switch support to the BJP. This is despite the fact that they were *less* likely to receive state benefits than Hindu households, a phenomenon that intensified after 2013 (see Table A16 in the Appendix). This suggests that factors other than welfare benefits explain why they were less likely to switch support from the TMC to the BJP, in line with the hypotheses stressing the growing importance of voting based on identity (religion and migration status).

Next, we verify that these patterns are robust to controlling for benefits received, demographic characteristics and land ownership. Table 9, shows regression coefficients γ_{pt} of

[29] The analysis in Section 7.2 uses data made available by the West Bengal state election commission for the entire state. TMC candidates ran unopposed in approximately 33% of seats. Given how strongly contested local elections in West Bengal usually tend to be, we take this as a measure of the political violence and intimidation by TMC party activists.

[30] Households are defined as migrants if they relocated to the village after 2003.

Figure 5: 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.

voting propensities in 2013 and 2018 of the indicator variables for household socio-economic categories. It shows that in 2018, non-Hindu households were 20 percentage points more likely than native Hindu households to vote for the TMC, and 16.7 percentage points less likely to vote for the BJP. These patterns strengthened significantly between 2013 and 2018.[31] Conversely, even though they received more state benefits than non-Hindus, scheduled caste (SC) and scheduled tribe (ST) households were less likely to vote for the TMC

[31] Different socio-economic groups may also have differing vote responses to receiving welfare benefits. Table A17 in the Appendix shows that non-Hindus were less responsive to the receipt of state benefits in 2018 than in 2013, and non-responsive to central benefits. Even if they did not receive any benefits in 2018, they were significantly more likely to vote for the TMC (by 23.6 percentage points) and significantly less likely to vote for the BJP (by 18 percentage points) than Hindus were; in 2013 these patterns were much weaker. In other words, non-Hindus appear to have become an increasingly secure vote-bank for the TMC, despite receiving smaller shares in the welfare benefit allocation.

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 Households	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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

in 2018 than general caste or OBC households were; this effect is statistically significant for ST households. Hence we see asymmetric voting patterns across religion and caste lines, even after controlling for benefits received and a range of other demographic characteristics, suggesting that non-economic factors such as religious, immigrant and ethnic identity played an important role.

Finally, we consider a welfare-program-based explanation for why Hindus and SC/STs may have been more likely to switch their votes to the BJP than non-Hindus. The explanation is based on the idea that in 2018 the former groups voted for the BJP partly as a reaction to the TMC's "appeasement" of Muslims and immigrants. As per this hypothesis, these voters may have responded not only to their own benefits but also those distributed to non-Hindus. Specifically, controlling for the benefits that they themselves received, Hindus with an animus against non-Hindus may have voted against the TMC if the TMC distributed more benefits to non-Hindus. Our data do not allow us to test directly whether Hindu voters *perceived* that Muslims or more specifically, Muslim immigrants were being appeased. However, as we show in Table A16 in the Appendix, the data provide no support for the idea that Muslims disproportionately received more benefits than Hindus. Even after controlling for landownership and household demographic characteristics, there was no differential in the likelihood that non-Hindus and Hindus received either state or central benefits.

8 Concluding Comments

To summarize, we find no evidence that the new central benefit schemes were better targeted than older state benefit programs to poorer or SC/ST households, or that the targeting of state programs improved after 2014. There is also no evidence of a decline in regional clientelism after 2014. While funding for some state programs such as NREGS shrank after 2014, the overall quantum of state benefits remained similar to before, since the TMC expanded the scale of other state benefit programs. Moreover, NREGS and state programs generally retained or increased their effectiveness at generating votes for the state-level incumbent. Thus post-2013 changes in the scale and effectiveness of different welfare programs cannot explain the ascendance of the BJP in West Bengal. Our data suggest that the dramatic rise of the BJP's vote share also cannot be explained by a general anti-incumbency trend or backlash against the TMC associated with declines in farm or employment earnings, political violence in the 2018 local government elections, or "appeasement" of Muslims and immigrants in the distribution of welfare benefits. Instead, the fact that support for the BJP mainly grew among Hindus, even after controlling for the receipt of welfare benefits, suggests that ideological and social identity considerations have played an important role.

Our results are consistent with the arguments from the previous all-India level literature that new benefits introduced by the BJP-led central government have further helped it increase the BJP's vote share. Since we do not detect clear differences in the targeting performance of central and state benefits, this can possibly be explained by the BJP's greater success at claiming credit for the new central programs. However, welfare benefits generated only small positive effects on the BJP's vote share, and they were often not statistically significant. Presumably this is because local governments retained control over some key aspects of central benefit distribution, which allowed them to also receive credit for the schemes.

Our findings are also consistent with a number of other recent articles on West Bengal politics that draw attention to the TMC'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 in an environment of fluctuating and uncertain earnings, the structural characteristics of West Bengal's rural labour market and the low female labour force participation rate ensure that the electorate continues to rely on transfers from the state government to stabilize household incomes, which allows clientelism to perpetuate. Nath (2022) provides data and ethnographic evidence that since 2011, the TMC has increasingly wooed the minority vote by encouraging religious and cultural celebrations and the use of traditional community-based mechanisms of dispute settlement.

Data limitations prevent 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. Readers may also worry that our findings are specific to West Bengal and do not apply to other Indian states. They are unlikely to apply to other parts of the country where the state government was either controlled or aligned with the BJP, and therefore did not witness competition between the BJP and regional incumbents. However they might be relevant to eastern and southern states of India where regional and local governments were engaged in active competition with the BJP, and where the BJP had limited presence or party organization before 2014. An examination of whether this was actually the case will have to await further research.

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