When Representation Fuels Protest:
Evidence from India

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Abstract

Protests and political representation are often seen as substitutes. This idea underlies prominent theories that explain democratization as a way to prevent uprisings, and receives empirical support from historical enfranchisement episodes. Using the recent legislation of the Citizenship Amendment Act (CAA) in India – a law perceived to *disenfranchise* Muslims – and the subsequent CAA protests, we show that representation can also play a *complementary* role in facilitating protests. Employing a close election regression discontinuity design we find that having a Muslim state representative significantly increased the likelihood of a CAA protest in their constituency, but did not affect the likelihood of other protests. The result is not driven by party identity or incumbency of the legislator. This complementarity is weaker in states with a higher share of Muslim legislators, especially when they are in the state's ruling coalition, possibly because in this case legislators can directly influence public policy.

1 Introduction

Protests and political representation are often viewed as substitutes. This idea underlies prominent theories of democratization which highlight that democratization (and hence, representation) works as a way to prevent uprisings from unrepresented and disaffected citizenry (Acemoglu and Robinson 2000; Aidt and Franck 2015; Cederman et al. 2010). Political representation helps citizens express their preferences to policymakers via institutional mechanisms, which in turn can affect policy (Chaturvedi et al., 2025) and public resource allocation (Cascio and Washington, 2014). This reduces the incentive to take the more costly action of protest or political violence. Empirical evidence in favor of the negative relationship between representation and protest or political violence often draws on enfranchisement episodes that made political representation more inclusive. Marcucci et al. (2022), for example, show that political violence decreased as a result of franchise extension in the context of the UK's Representation of the People Act of 1867. The authors find higher anti-incumbency (i.e., new political representatives coming to power) as one of the mechanisms behind the reduction in conflict. Lacroix (2023) similarly finds negative effect of enfranchisement on political violence in the context of the US Voting Rights Act of 1965.

There may, however, exist an asymmetry between enfranchisement and disenfranchisement. Once in office, established political representatives can *facilitate* protests by providing organizational capital and coordination service to the protesters, as (non-violent) protests are not outlawed (at least not yet). Representatives may be especially motivated to do so if they are unable to affect policy changes through institutional mechanisms. In such a context, they can utilize costly protests as informative signals about voter dissatisfaction to shore up support for their desired policy change. In turn, minority or threatened groups may perceive higher expected gains to protesting in the presence of representatives who can help channel the protests into policy.

In this paper we provide an analysis of the relation between representation and (mostly non-violent) protests under the specter of disenfranchisement. Threats to citizenship rights and the consequent disenfranchisement of specific groups is a growing concern across the world (Bhat and Shahid, 2024). The American Bar Association has recently highlighted the enactment of various election laws across several states in the US as restrictive of voter access, effectively targeting voting rights of specific communities. Hungary has recently amended its constitution to allow 'suspension of citizenship rights' for dual nationals, which many perceive as a tool to silence critique of the ruling government.[1]. Similar rules of curtailment and revocation of citizenship rights have been implemented in Turkey[2] and Myanmar (Lee, 2019). In India, the enactment of the Citizenship Amendment Act (CAA) in 2019 was widely perceived as a threat to the citizenship rights of Indian Muslims, and was followed by widespread nationwide protests (see Section 2). The fact that the CAA was seen as threatening a large and well-identified group, and that both the local political representation of that group and the extent of the protests can be directly observed, makes this case particularly suitable for studying the substitutability between representation and protest. India being the largest democracy in the world, it is also important in its own right.

We hand-collect data on the location and date of CAA protests along with other details. We map the protest locations to Assembly Constituencies (ACs) that elect the state legislators to the state assemblies.

[1] https://www.politico.eu/article/hungary-could-suspend-citizenship-to-silence-dissent/
[2] https://www.statelessness.eu/sites/default/files/2022-11/ENS-ISI_UPR20Turkey.pdf

Eleven percent of ACs in India experienced at least one CAA protest. We then employ a close-election regression discontinuity design to compare, within the same state, ACs that barely elected a Muslim legislator with those that barely elected a non-Muslim one.

The evidence suggests strong complementarities between political representation and protests. We find that the presence of a Muslim legislator increases the likelihood of any CAA protest in the Assembly Constituency by around 18 percentage points. We obtain similar results when using an alternative independent data source (ACLED) on protests to identify the CAA protests in India. Importantly, we find no effect of electing a Muslim legislator on the likelihood of other, non-CAA, protests.

To interpret this effect, note that a close election victory of a Muslim candidate against a non-Muslim one could also result in discontinuous changes in other characteristics of the AC's representative, which in turn could potentially affect the likelihood of protest. While we find no discontinuity in gender, age and incumbency rates, Muslim winners are discontinuously less likely to be affiliated with the BJP—the ruling party at the national level—and more likely to be from the Indian National Congress (INC), the other large national party. They are also less likely to be aligned with the ruling party in the state. The Muslim legislator treatment effect might therefore be partly driven by the party identity of the winner. To test this, we estimate the causal effects of BJP, INC and ruling party legislators on the probability of CAA protests, using analogous close election RDDs (with the margin of victories for BJP, INC and ruling party as the running variables, respectively). We find precisely estimated null effects in all of these cases.

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We hypothesize that in a state with a higher share of Muslim legislators, it would be easier for them to directly negotiate with the state government due to being a stronger bargaining block, making protests instrumentally less valuable at the margin. Hence, we expect the complementarity force to be stronger in states with low share of Muslim legislators. Consistent with this, we find that the treatment effect reduces significantly in states with higher share of Muslim legislators.[3] Moreover, the negative interaction effect is stronger when the Muslim legislators are in the ruling coalition of the state government rather than in the opposition, making direct negotiation less costly for them. The majority of Muslim legislators in Indian states were in the opposition at the time of CAA protests. Hence, the logic of complementarity was more salient for them as opposed to the substitutability channel. Hence, we observe the positive effect of representation on average.

We find no differential treatment effect in BJP ruled states, suggesting that protection from state repression during protests was not the primary driver of the treatment effect. The treatment effect is also not larger in ACs with higher electorate share of Muslims. This undercuts the argument that Muslim legislators may have been motivated to mobilize protesters with an aim for electoral gains in the next election, since such gains are presumably higher in ACs with a larger share of the aggrieved voting group. The treatment effect, however, is significantly higher in ACs where Muslims are spatially concentrated. This is consistent with the idea that Muslim legislators helped coordinate the protesters, since the marginal effect of coordination effort is higher if the group members live closer to each other. We do not find evidence that Muslim legislators with stronger political capital (incumbents) or higher experience (seniority in age) have higher treatment effects.

[3] In spite of the negative interaction effect, the overall association between state level occurrence of CAA protests and Muslim legislator share is positive and statistically significant, as mentioned in Section 3.1.

Our work contributes to the understanding of the relationship between political representation and protest or political violence. Our results highlight that whether the relationship is positive or negative depends on the political context, specifically the extent to which representatives can influence the decision-making of the government. Some recent papers show how coordination technology can facilitate protests. Enikolopov et al. (2020) show that social media helps to coordinate actions rather than providing information leading to protest. Manacorda and Tesei (2020) show that adoption of mobile phones leads to increased chances of mass protests at the time of economic downturn. We add to this by showing that elected representatives can provide leadership by way of coordination in facilitating protests. This is consistent with Gethin and Pons (2024) who use data on the quasi universe of protests in the US to argue that protests that lack a stable leadership fail to shift electoral behavior or political attitudes of voters. Gillion (2012), on the other hand, find that protests in the US were effective in shaping the way legislators voted in the US Congress. Aidt and Franck (2019) similarly find that peaceful protests, as opposed to violent agitation, were more effective in influencing legislator behavior in the context of the Great Reform Act in the UK.

The literature on strategic protest participation has examined whether such participation are strategic substitutes or complements (Shadmehr and Bernhardt (2011)). Cantoni et al. (2019) find evidence for substitutability in the pro-democracy protests in Hong Kong, while González (2020) finds that the student protests in Chile exhibit complementarity. We add to this discussion by pointing out that mobilization incentive of the elected representative and protest participation can also exhibit strategic complementarity.

2 Institutional Background and Context

State Elections and State Representatives State elections in India are held every 5 years (different states may hold elections in different years). Each state is divided into Assembly Constituencies (ACs), and one legislator is elected from each AC. The elections employ a first-past-the-post system, i.e., the candidate receiving the highest number of votes in each constituency is elected, regardless of whether they secure an absolute majority. The legislators are referred to as the Members of Legislative Assembly, or MLAs. The number of MLAs, i.e., the size of the state assembly, differs from state to state in accordance with their population. A large state like Uttar Pradesh has 403 MLAs, while Sikkim has 32. Overall, there are about 4,500 MLAs across the country. The local MLA in the AC is an important political representative in the area, responsible for implementation of various public projects as well as for voicing the concerns of local population to the state government.

The Citizenship Amendment Act. In December 2019, the Indian Parliament passed The Citizenship (Amendment) Act (CAA), which amended India's citizenship law to provide an expedited path to citizenship for persecuted religious minorities from Afghanistan, Bangladesh, and Pakistan who entered India before December 31, 2014. Significantly, the Act specified six religious communities – Hindus, Sikhs, Buddhists, Jains, Parsis, and Christians, but excluded Muslims. The controversy surrounding the CAA intensified due to its perceived connection with the National Register of Citizens (NRC). The NRC was not a new concept – it was mandated by the 1955 Citizenship Act and first implemented in Assam between 2015-2019 following a 2013 Supreme Court order. However, in November 2019,the govern-

ment announced plans to implement a nationwide NRC. The NRC requires residents to prove their citizenship through ancestral documentation showing their family's presence in India before some cut-off date. Many residents, particularly those from marginalized socioeconomic backgrounds, lack access to such historical documentation as birth certificates, land records, or ancestry proof. In Assam's NRC implementation, approximately 1.9 million residents found themselves excluded because they couldn't provide sufficient documentary evidence.

While the government maintained that the CAA and NRC were separate initiatives, opposition leaders and public commentators argued that their combined effect would create a system where non-Muslim individuals without documentation could claim citizenship under the CAA's provisions, while Muslims in identical situations would have no pathway to citizenship. From this perspective, non-Muslims excluded from the NRC could still gain citizenship through the CAA pathway, while Muslims excluded from the NRC faced potential statelessness, detention, or deportation without any safety net.

The Anti-CAA Protests. The legislation sparked widespread protests across India. Protesters took to the streets condemning what they saw as an attack on the constitutional principle of equality. Muslim communities played a prominent role in organizing and sustaining these demonstrations, viewing the CAA-NRC combination as directly threatening their citizenship rights. Protesters often cited Article 14 of the Indian Constitution, condemning what they saw as religious discrimination. The protests spread across major Indian cities beginning in December 2019, with notable demonstrations at various universities. While many protests remained peaceful, some areas experienced violence resulting in property damage and casualties. The government response included internet shutdowns, prohibitory orders, and police actions in several states, which in some cases led to further escalation. Partly in response to the protests, several state assemblies passed resolutions not to implement the CAA in their state.

The protests largely subsided by March 2020 due to the COVID-19 pandemic and resulting lockdowns. In December 2023, the Supreme Court of India upheld the constitutional validity of the CAA, rejecting over 200 petitions challenging the law. The government finally issued rules for implementing the CAA in March 2024 but, at the time of writing, a nationwide NRC has not yet been implemented. The CAA-NRC issue remains politically significant, particularly for India's Muslim population, with ongoing debates about its implications for India's constitutional framework.

3 Data

Protest Data: We manually compile data on CAA-NRC protests using news reports and social media sources. We consider the information shared on social media only when it was accompanied with photographs and/or videos. We restrict attention to English language news reports. The event search covers the period from December 2019 when the protests erupted, to March 2020 when the Covid induced lockdown began. For each protest documented, we record its location and manually match it to a census district and an Assembly Constituency (AC). Additionally, we record its date and type of protest (whether a rally/march or a sit-in protest).[4] In total, we have information about 1,025 CAA-NRC protests.

[4]We also record the size of the protest. However, this information is often missing. We therefore do not analyze it.

We also examine the robustness of our results using an alternative protest data source - the Armed Conflict Location and Event Data or ACLED (Raleigh et al., 2010). ACLED contains information on day-level conflict and protest events across the globe along with geocoded location and a description of the event. The dataset has been used widely to study conflicts (Michalopoulos and Papaioannou, 2016; Premand and Rohner, 2024) as well as protests (Shuman et al., 2022; Rød et al., 2025; Lewis and Ives, 2025). The India related event data range from 2016-2024. We tag an event to be a protest if it is categorized as "Peaceful protest", "Protest with intervention" or "Violent demonstration". Additionally, we identify a CAA-NRC protest as those protests containing the phrases "CAA", "NRC" and "Citizenship Amendment" in its description (recorded in the 'notes' column). The ACLED data record about 3000 CAA-NRC protest events, less than 5% of which are coded as violent. Consistent with the way the events unfolded, and in line with our manual data collection procedure, 86% of the ACLED CAA-NRC protests are in 2019 and 2020, while the rest are in 2021 or later. However, since ACLED codes protests in different days as separate events, it provides an over-estimate of the number of unique protests.[5] One advantage of the ACLED data, however, is that it also provides information on non-CAA protests. We match the ACLED protests to ACs using the location of the protests along with the AC shape files.

Election Data: To identify the political representatives at the time of the protests, we access the data on state assembly elections held across all states during the period 2015-2019 from the Trivedi Center for Political Data at Ashoka University (Jensenius and Verniers, 2017).[6] The data contain candidate level election results, with candidate name, party affiliation, vote tallies in each AC along with total number of registered voters or electors and turnout in the AC. We use the religion prediction ML algorithm proposed by Chaturvedi and Chaturvedi (2024) to identify the Muslim and non-Muslim candidates. This allows us to identify ACs that had a Muslim representative or MLA at the time of CAA protests.

Voter Religion Data: The data on AC level voter characteristics, specifically, religion-wise number of voters is not readily available.[7] We therefore use the data on estimated AC level Muslim electorate share prepared by one of the authors as part of a different project. The estimation uses a 3 percent (AC level) random sample of voters from the list of all registered voters in India in 2018 that have been digitized by a private firm and applies the aforementioned ML algorithm of Chaturvedi and Chaturvedi (2024) to predict voter religion. This yields reliable estimates of Muslim electorate share across ACs. Additionally, we also use estimates of pin-code level Muslim electorate share within each AC, which allows us to measure within AC spatial concentration of Muslim electorate.[8] We use this measure to analyze a potential mechanism of our observed effects.

[5] Sit-in demonstrations running for several days were common during the CAA-NRC protests. In our hand-coded data, which counts only unique protests as separate events, 21% of protests are sit-in in nature. This is a potential reason for the higher count in ACLED.

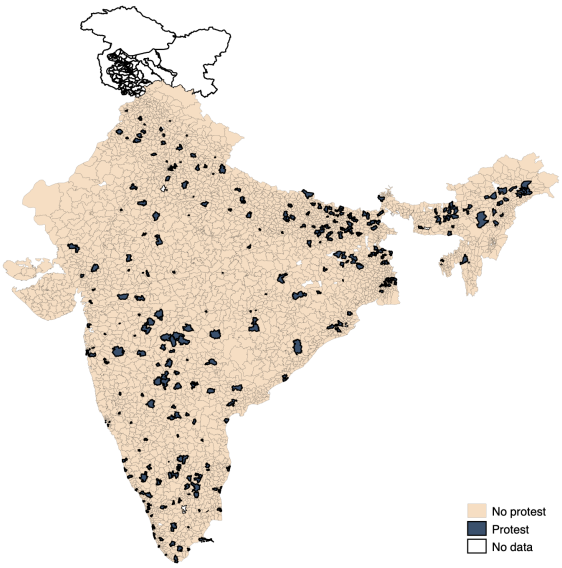
[6] We drop the state of Jammu and Kashmir from the sample since it was reorganized as Union Territories in August 2019, resulting in the loss of power of the sitting political representatives.

[7] Census 2011 provides religion-wise population at the sub-district (*Tehsil*) level, which map imperfectly to AC boundaries. Moreover, the population numbers can differ from voter numbers for various reasons.

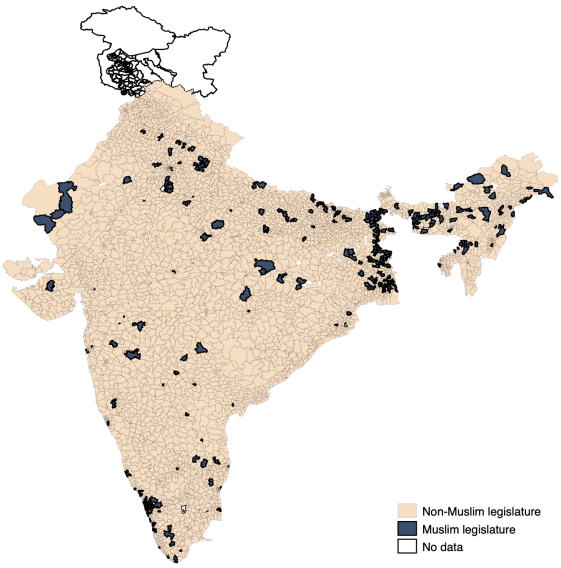
[8] The voter sample contains pin-code information for each voter. Pin-code areas can cross AC boundaries. We use the voter sample within in each AC to compute the Muslim shares for each pincode-AC pair.

Figure 1—CAA Protests and Muslim Representation in 2019

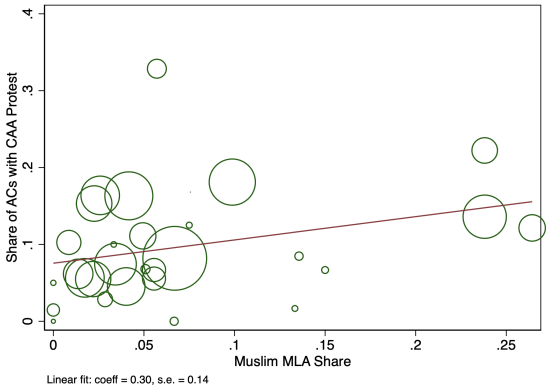
(a) CAA Protests: ACs



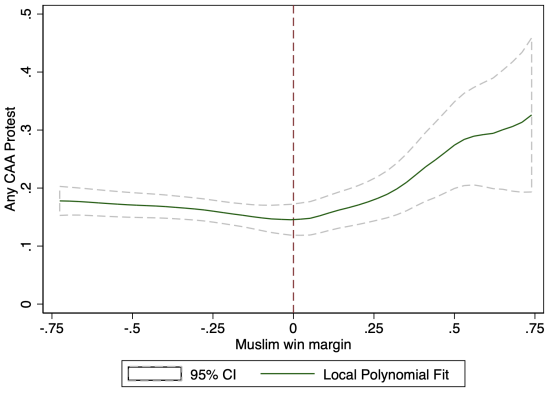
(b) Muslim Representation: ACs



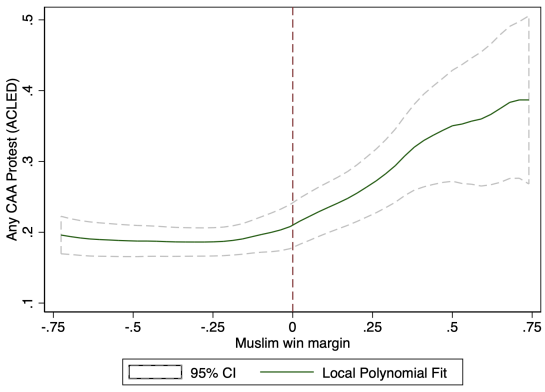
(c) CAA Protests across States



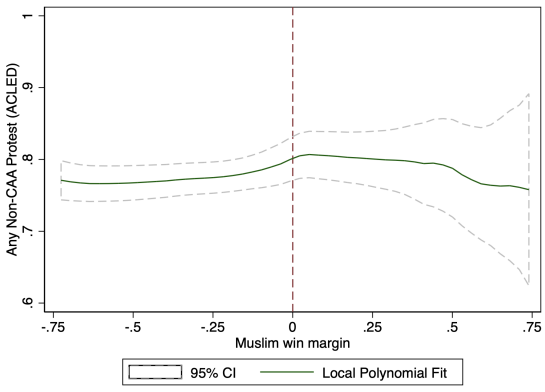
(d) CAA Protests by Muslim Win Margin



(e) CAA Protests by Muslim Margin (ACLED)



(f) Non-CAA Protests by Muslim Margin



Notes: Panel (a) shows the Assembly Constituencies (ACs) that experienced any CAA protest (mean = 0.11). Panel (b) shows the ACs that had a Muslim representative at the time of CAA protest, i.e., by end of 2019 (mean = 0.07). Panel (c) shows the state level correlation between the share of Muslim legislatures in 2019 and the share of ACs having any CAA protest. Panel (d) shows the local polynomial relationship between Muslim win margin and whether the AC had any CAA protest in the full sample. Panel (e) is the same graph using ACLED as a source for protest data. Panel (f) is the same graph using non-CAA protests as outcome.

3.1 Descriptive Statistics

For each AC, our main outcome variable is an indicator of whether *any* CAA protests occurred in the AC. We therefore consider the extensive margin of protest occurrence as our main outcome. First, in our hand-coded data, 11% of ACs observe any CAA protests. (It is 17% in ACLED.) Therefore, most ACs did not see any CAA protests, making the event important for analysis. Moreover, variation in the number of protests across ACs could be partly driven by measurement error with capturing all the protests in our data. The indicator of any protest is potentially less susceptible to this error.[9] Figure 1a depicts the spatial map of ACs with any protest across India. We observe that the protests were not geographically concentrated and were spread throughout the country. Figure 1b shows the ACs with Muslim and non-Muslim MLAs. At the time of protests, 7.5% of MLAs in the country were Muslims.

Figure 1c graphically shows the correlation across states between the share of Muslim MLAs and the share of ACs with any CAA protest. Each circle in the graph is a state, with the circle size depicting its 2011 population. The correlation is positive and statistically significant at 5%. The regression coefficient is 0.3 (s.e.= 0.14), implying that moving from a state with no Muslim MLA to a state with 25% Muslim MLAs would increase the share of ACs with any CAA protest by 7 percentage points, a strong association given the mean of 0.11. However, the correlation need not necessarily depict a causal relationship. States with higher share of Muslim MLAs could also have higher share of Muslim population, or have a higher sense of aggrievement with the CAA-NRC legislation among its voters etc. Hence, it is difficult to infer from aggregate patterns across states whether Muslim MLAs facilitated CAA protests.

To motivate the case that Muslim representation may have been important in this case, we depict in Figure 1d a local polynomial relationship at the AC level between the Muslim win margin in that AC (as defined above) and the indicator of any CAA protest in the full data. As the graph shows, the relationship is initially flat when Muslim win margin takes negative values, i.e., in ACs with non-Muslim MLAs, but turns significantly positive for ACs with Muslim MLAs. This pattern gets replicated with ACLED data on CAA protests (Figure 1e), but not with non-CAA protests (Figure 1f). A much larger fraction of ACs experienced any non-CAA protests in 2019 or after. But we find no discernible relationship between Muslim win margin and likelihood of any non-CAA protest. This suggests that Muslim representation may have played a role in facilitating the CAA protests.

4 Estimation Strategy

To identify the causal effect of the religious identity of the state legislature on protest probability we focus on close elections between Muslim and non-Muslim candidates and deploy the close election regression discontinuity (RD) design. This is now a standard method in political economy to estimate the treatment effect of political representative on downstream outcomes (Nellis et al., 2016; Bhalotra et al., 2018; Lehne et al., 2018; Mahadevan, 2024). For each AC a in state s, we compute Muslim win margin ($m_{a,s}$) as the difference between the vote shares (v_c) of the highest vote receiving Muslim and non-Muslim candidates (c):

$$m_{a,s} = \max_{c \in \mathcal{M}_{a,s}} v_c - \max_{c \in \mathcal{N}_{a,s}} v_c$$

[9] This can happen if the likelihood of a protest event in an AC being covered in news or social media is negatively affected by the number of other protests happening in the AC (due to limited news space or attention).

where $\mathcal{M}_{a,s}$ and $\mathcal{N}_{a,s}$ are the sets of Muslim and non-Muslim candidates in AC a in s, respectively. We define the variable this way since there may be several Muslim and non-Muslim candidates in an AC. The Muslim win margin is positive in ACs where a Muslim won and is negative in the other case. Smaller magnitudes of the Muslim win margin implies that the AC had a tighter election between Muslim and non-Muslim candidates. Figure 2a shows the distribution of Muslim win margin. We observe that the density is continuous at zero. The variable therefore passes the McCrary test which tests for manipulation of the running variable by estimating discontinuity in its density.

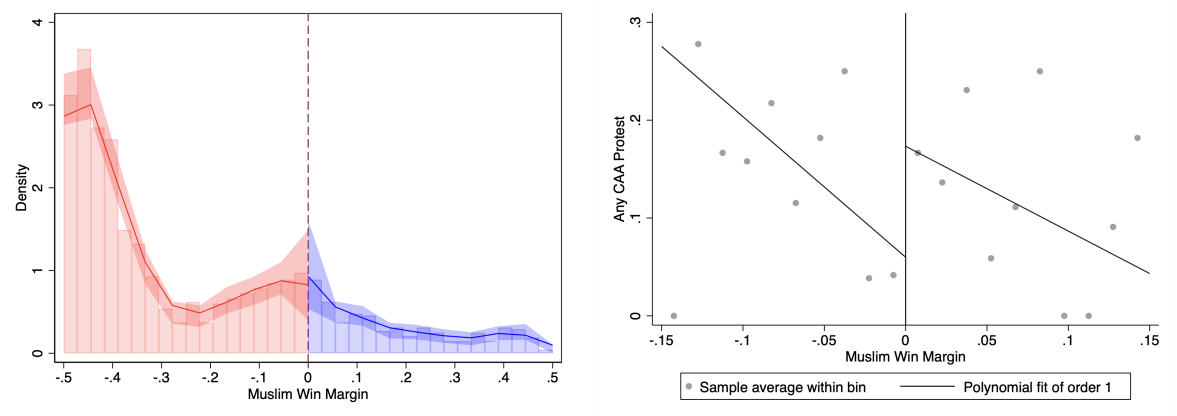
For estimation, we select ACs with Muslim win margin within some bandwidth, $m_a \in [-h, h]$, and estimate the following relationship:

$$\text{Any CAA Protest}_{a,s} = \phi_s + \gamma \mathbb{I}[m_{a,s} > 0] + f(m_{a,s}) + f(m_{a,s}) * \mathbb{I}[m_{a,s} > 0] + \epsilon_{a,s} \quad (1)$$

where Any CAA Protest$_{a,s}$ is the dummy variable indicating whether AC a in state s had any CAA protest, ϕ_s is state fixed effect, $f(\cdot)$ is the control function and $\mathbb{I}[m_{a,s} > 0]$ indicates whether the Muslim win margin is positive in a, i.e., whether a has a Muslim MLA. As default we use linear control function for our estimation, and show robustness using a quadratic specification. We select the optimal bandwidth for the main outcome variable using the MSERD approach proposed by Calonico et al. (2014) and fix the bandwidth for all our analysis.

5 Results

Figure 2—McCrary Test and Regression Discontinuity Plot



(a) McCrary Test

(b) CAA Protest: RD Plot

Notes: Panel (a) shows the density of the Muslim margin of victory and Panel (b) shows the regression discontinuity estimation (using the `rdplot` command) using linear fits (and state fixed effects) on both sides of the Muslim win margin cut-off value of zero and binned values of the variables.

Table 1 reports the results. In all columns we report the bias-corrected RD estimates with robust standard errors, estimated using the `rdrobust` command (Calonico et al., 2017). Columns (1)-(4) report the results using the hand-coded data, while columns (5)-(8) report the same results using ACLED. Column (9) shows the results for any non-CAA protest (using ACLED). For each data source, we show the result first without and then with state fixed effects (first two columns), then change the control func-

tion from linear to quadratic (third column) and finally, reduce the bandwidth by half (fourth column). For each data source, all the RD estimates are positive and statistically significant across the four specifications. For the hand-coded data, the estimates range from 0.15 (column (1)) to 0.51 (column (4)). This is a large effect considering the sample mean of 0.14. For ACLED, the estimates range from 0.17 (column (1)) to 0.25 (column (4)), with a sample mean of 0.20. Therefore, the result is robust across datasets and specifications. For our preferred specification (linear control and state fixed effect), the estimated effect is 0.18 (hand-coded data) or 0.20 (ACLED), both of which are statistically significant at 5%. Figure 2b graphically shows the discontinuity using a linear fit on the hand-coded data. We find that conditional on a close election between a Muslim and a non-Muslim candidate, electing a Muslim MLA has a statistically and economically significant causal effect on CAA protest probability. The RD estimate for any non-CAA protest in column (9) is -0.01 (s.e. = 0.08), with a sample mean of 0.80. Therefore, we do not find that electing a Muslim MLA has any causal effect on non-CAA protest probability. Therefore, the observed effect on CAA protests is not due to an overall increase in all types of protests.

Table 1—Effect of Electing Muslim Legislator on CAA Protest Probability

	Hand-coded data						ACLED				
	Any CAA Protest				Any Sit-in	Any Rally	Any CAA Protest				Any Non-CAA Protest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Muslim Winner	0.15*	0.18**	0.24**	0.51***	0.11**	0.18**	0.17*	0.20**	0.17*	0.25**	-0.01
	(0.08)	(0.07)	(0.10)	(0.13)	(0.05)	(0.07)	(0.10)	(0.08)	(0.10)	(0.11)	(0.08)
Mean Dep. Var.	0.14	0.14	0.14	0.14	0.05	0.13	0.20	0.20	0.20	0.20	0.80
Effective Obs	300	300	300	168	300	300	300	300	300	168	300
Bandwidth (h^*)	0.118	0.118	0.118	0.059	0.118	0.118	0.118	0.118	0.118	0.059	0.118
Polynomial order	1	1	2	2	1	1	1	1	2	2	1
State FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes

Notes: The table reports regression discontinuity estimate using Muslim margin of victory in Assembly Constituencies (ACs) of Indian states as the running variables. The Muslim margin of victory is calculated for the last election prior to the 2020 CAA protests. Columns 1-6 use hand-coded protest data to compute the dependent variables, while columns 7-11 use ACLED. The dependent variable in all columns except columns 5, 6 and 11 is a dummy that takes value one if any CAA protest happened in the AC and is zero otherwise. In column 5, it is an indicator of any CAA sit-in protest and in column 6, it is an indicator of any CAA rally. In column 11, the dependent variable is an indicator of any non-CAA protest. We use CCT optimal bandwidth for column 1, and fix the bandwidth for the other columns for ease of comparison. Column 1 has no co-variates and linear control function, column 2 adds state fixed effects, column 3 additionally makes the control function quadratic, and column 4 further reduces the optimal bandwidth by half. The columns 7-11 have the same sequence of specification. Robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1

Co-variate Balance: We test for discontinuity in various AC level election related variables and pre-existing characteristics. Appendix Table A1 reports the RD coefficients for these variables using the same bandwidth used in Table 1. The top panel of the Table shows the results for the total number of registered voters or electors (column (1)), number of candidates (column (2)), turnout rate (column (3)), share of female candidates (column (4)), average age of the candidates (column (5)), the effective number of parties, defined as the inverse of the Herfindahl–Hirschman Index of the vote shares of the candidates (column (6)) and the share of Muslim in the electors (column (7)). In each case, the RD coefficient is statistically insignificant. In the bottom panel, we use seven AC level population charac-

teristics, such as share of minority caste (SC) population, sex ratio, employment share, landholding etc. We access this from SHRUG database. The information is not available for all the ACs, resulting in a smaller sized sample for these estimations. We do not find any significant discontinuity for any of the variables. This indicates that the ACs around the threshold are comparable across a number of economic and political characteristics.

Robustness: We have already observed that the main result is robust to quadratic control function specification and a smaller bandwidth. Appendix Table A2 shows the robustness of the result to dropping major states from the sample. In Panel A, we drop major states from the Northern and Eastern region of India and in Panel B we drop major Southern and Western states. Panel A column (1) reproduces the main result from Table 1. In the subsequent columns we drop ACs from Uttar Pradesh, West Bengal, Assam and Bihar. In the last column we drop ACs from all these states at the same time. We find that our main result remains robust to dropping these states. Panel B drops ACs in Maharashtra, Karnataka, Andhra Pradesh, Kerala and all the states together. The result remains robust in this case as well.

Table 2—Differential Characteristics of Muslim Winners and Their Effects on CAA Protest Probability

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
	Female	Age	BJP	INC	Incumbent	Ruling Party
Muslim Winner	0.02	-1.26	-0.50***	0.24***	0.09	-0.41***
	(0.06)	(2.45)	(0.09)	(0.07)	(0.10)	(0.11)
Mean dep. var.	0.09	52.33	0.31	0.18	0.49	0.53
Observations	300	271	300	300	300	300
Bandwidth (h^*)	0.118	0.118	0.118	0.118	0.118	0.118
Polynomial order	1	1	1	1	1	1
State FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B			
	Any CAA Protest (BJP)	Any CAA Protest (BJP)	Any CAA Protest (INC)	Any CAA Protest (INC)	Any CAA Protest (Ruling)	Any CAA Protest (Ruling)
BJP/INC/Ruling Party Winner	-0.04	-0.03	-0.00	0.00	-0.01	-0.01
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Observations	1365	1365	1210	1210	1728	1728
Bandwidth (h^*)	0.118	0.118	0.118	0.118	0.118	0.118
Polynomial order	1	1	1	1	1	1
State FE	No	Yes	No	Yes	No	Yes

Notes: Panel A of the table reports RD estimates using Muslim margin of victory in Assembly Constituencies (ACs) of Indian states as the running variable. The dependent variables are various characteristics of the winners – indicator of gender (coulmn 1), age (column 2), whether party is BJP (column 3), INC (column 4), indicator of incumbency (column 5) and whether winner belongs to the ruling coalition (column 6). All columns have state fixed effects and use CCT optimal bandwidth used for column (1) of Table 1. In Panel B, the dependent variable is the indicator *Any CAA Protest* for all columns. The running variables are the margin of victory for BJP in columns 1-2, for INC in columns 3-4 and for the ruling party in columns 5-6. Odd numbered columns do not have any controls while even numbered columns have state fixed effects. Bandwidth is kept the same as Panel A for ease of exposition. All results robust to using CCT optimal bandwidths for each column. Robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1

Alternative Interpretation: The treatment effect estimated in Table 1 could be driven by some other characteristics of the winning candidate that also change discontinuously at the Muslim win margin threshold. This can happen if Muslim candidates have different party affiliations and personal characteristics, especially in the close election sample. Table 2 Panel A tests for discontinuity at the Muslim win margin threshold of the winner's gender (column 1), age (column 2), party affiliation to BJP (column 3) and INC (column 4) – the two largest national parties, incumbency (column 5) and whether the winner belongs to the state's ruling party or coalition post election (column 6). We do not find statistically significant discontinuity for gender, age and incumbency. There is however statistically significant discontinuity in the likelihood of the winner being affiliated to BJP and INC. Muslim winners are 50 percentage points less likely to be a BJP candidate and 24 percentage points more likely to be from INC. This makes sense given that BJP has a significantly lower support compared to INC among Muslim voters. We also find that Muslim winners are 40 percentage points less likely to belong to state's ruling party. Our estimated treatment effect could therefore be due to discontinuous changes in party affiliation and political alignment to ruling party.

Panel B of Table 2 estimates the causal effects on CAA protest probability of discontinuous changes in party affiliation and ruling party alignment. In columns 1 and 2, we use BJP margin of victory to test whether electing a BJP MLA causes any change in the CAA protest probability. Column 1 does not have any state fixed effects while column 2 does. Similarly, columns 3 and 4 test for discontinuity at the INC win margin and columns 5 and 6 test it for the ruling party margin of victory.[10] We find that the RD estimates in all the columns are small in magnitude and are statistically insignificant.[11] Therefore, there is no evidence that BJP or INC representatives or those who belong to the state's ruling party affects CAA protest probability. Therefore we are confident that the treatment effect estimated in Table 1 is indeed driven by the religious identity of the representative.

6 Mechanisms

To explore the mechanisms, we examine heterogeneity in treatment effect across states, ACs and legislators using the difference-in-discontinuity approach (Khanna and Mukherjee (2023); Das et al. (2021)). For a differencing variable D_s defined at the state level, say, we estimate the following specification:

$$\begin{aligned}\text{Any CAA Protest}_{a,s} = \phi_s + \gamma\mathbb{I}[m_{a,s} > 0] + \delta D_s * \mathbb{I}[m_{a,s} > 0] + \theta D_s \\ + \beta_1 m_{a,s} + \beta_2 m_{a,s} \ * \ \mathbb{I}[m_{a,s} > 0] \\ + D_s\big\{\beta_3 m_{a,s} + \beta_4 m_{a,s} \ * \ \mathbb{I}[m_{a,s} > 0]\big\} + \epsilon_{a,s} \qquad (2)\end{aligned}$$

The coefficient δ estimates heterogeneous treatment effect. Table 3 report the results. Column (1) reproduces our baseline RD estimate from Table 1 for comparison.

Our conceptual framework suggests two ways in which other minority legislators affect the incentives of own constituency legislator to facilitate protests. First there may be free riding on the protests

[10] For each candidate we identify whether they belong to a party that became the ruling party or part of the ruling coalition post-election. The ruling party win margin is the difference between the vote shares of the winner and runner up in ACs where a ruling party candidate won, and it is the difference between ruling party candidate's vote share and the winner's vote share in ACs where the candidate lost.

[11] For ease of exposition we kept the bandwidth to be the same as Table 1. The results are robust to using MSERD optimal bandwidths for each column.

Table 3—Heterogeneous Effects of Muslim MLAs on Protest Probability

	CAA Protest							
	State Charac.				AC Charac.		Winner Charac.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Muslim Winner	0.18**	0.35**	0.35**	0.18*	0.31**	-0.01	0.21**	0.21*
	(0.07)	(0.14)	(0.14)	(0.09)	(0.14)	(0.07)	(0.10)	(0.11)
Muslim Winner * Muslim Legislator Share		-1.69**						
		(0.74)						
Muslim Winner * Muslim Legislator Share (Ruling Coalition)			-2.43***					
			(0.82)					
Muslim Winner * Muslim Legislator Share (Opposition)			-1.32					
			(0.80)					
Muslim Winner * BJP Ruled State				-0.07				
				(0.11)				
Muslim Share in AC					0.68*	0.42*		
					(0.37)	(0.24)		
Muslim Winner * Muslim Share in AC					-0.68			
					(0.45)			
Spatially Concentrated Muslims						-0.01		
						(0.09)		
Muslim Winner * Spatially Concentrated Muslims						0.29**		
						(0.14)		
Incumbent							0.06	
							(0.09)	
Muslim Winner * Incumbent							-0.11	
							(0.14)	
Senior								0.03
								(0.09)
Muslim Winner * Senior								-0.10
								(0.15)
Observations	300	298	298	283	283	298	298	298
Bandwidth (h^*)	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118
Polynomial order	1	1	1	1	1	1	1	1
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates using the difference-in-discontinuity method with Muslim candidates winning Assembly Constituencies (ACs) as the treatment variable. Column 1 reports the RD estimate from Table 1 column (2). The differencing variables in the next three columns are defined at the state state level – share of Muslim legislators in a state (column 2), shares of Muslim legislators who are in ruling coalition and opposition at the state level separately (column 3), whether the state is BJP ruled (column 4). The differencing variable in the next two columns are at the AC level – share of Muslim voters in AC (column 5) and whether the Muslim voters are spatially concentrated within the AC (column 6). The final two columns have interactions with winner characteristics – whether the winner was an incumbent (column 7) and whether the winner's age was higher than median (column 8). All specifications have state fixed effects. All columns use CCT optimal bandwidth used for column (1) of Table 1. Standard errors are clustered at the state level for columns (2)-(4) (since the differencing variable is defined at the state level) and robust standard errors are reported for the rest. *** p<0.01, ** p<0.05, * p<0.1

in other constituencies. That is, it may be that there is an anticipation that the more Muslim legislators there are in other ACs, the less there is a need for protest in own constituency.[12] Second, it may be that the bargaining power with respect to the state government is increasing with the number of other Muslim legislators, which incentivizes them to directly negotiate with the state government rendering protests less valuable – the substitution motive.

Column (2) examines how the effect varies with the overall share of Muslim legislators in the state assembly. Consistent with both mechanisms, the interaction term is negative and statistically significant at 5%. The estimate of δ implies that moving from a state with 5% Muslim legislator to another with 15% would reduce the treatment effect by 0.17, indicating significant heterogeneity. For a closer examination of the second mechanism, we break up Muslim legislator share into the shares that are in the ruling party or coalition in the state and in the opposition, and estimate the interaction effects separately for them. We hypothesize that if the substitution motive is present, then the interaction with ruling party

[12]Note there may also be free-riding incentives on the part of the protesters, but these are captured by the state fixed effect and the fact that we are comparing constituencies with similar voting composition around the RD threshold.

Muslim legislator share will be stronger (i.e., more negative) than that for the opposition. This is because it would be easier for the Muslim legislators who are politically aligned with the state government to negotiate directly with them, making the substitution motive stronger. Column (3) reports the result. The estimate of δ for the ruling coalition share is -2.32 and is statistically significant at 1%, while it is -1.32 and is statistically insignificant for opposition share. The difference between the two estimate is statistically significant at 1% (F-stat = 10.99). We therefore find evidence for the substitution motive at work in states with higher presence of Muslim legislators in the ruling coalition. At the time of CAA protests, 60% of Muslim legislators in Indian states were in the opposition. This limited their ability in most states to effectively influence the state government to resist CAA implementation. This explains the presence of complementarity on average. Column (4) examines whether the effect differs in states ruled by the BJP (the party that promoted the CAA legislation). While Muslim representation increases protest probability by 18 percentage points in non-BJP states, this effect is not significantly larger in BJP-ruled states. This suggests that our main finding is not driven by "supply side" forces as it is not limited to states under the rule of the party promoting the contentious policy. It also suggests that the positive treatment effect is not primarily due to the legislator's ability to protect from state repression of protests.

Muslim legislators could be motivated to facilitate protests for electoral gains in the next election since mobilizing protesters can help gain support among the aggrieved voters. To test this, columns (5) investigates heterogeneity in treatment effect with respect to the Muslim electorate share in the AC. If electoral motives are important, we expect the treatment effect to be stronger in ACs with a larger share of Muslim voters. Column (5) confirms that constituencies with larger Muslim electorate are more likely to experience protests, as expected. However, the interaction between Muslim winner and Muslim electorate share is negative and not statistically significant. We therefore do find supportive evidence in favor of this channel.

Column (6) provides suggestive evidence for our coordination mechanism. If Muslim voters are spatially spread over the AC area, then it may be difficult to mobilize them for protest, as citizens have to congregate in one place for demonstrations and rallies. Therefore, the legislator's coordination effort would be more fruitful if the Muslim voters are spatially concentrated within the AC. We measure spatial concentration of Muslims by utilizing data on the distribution of Muslim electorate share across pin-codes within each AC. Section 3 describes how this data is constructed. We then compute the dissimilarity index for each AC – a widely used measure of spatial concentration in the segregation literature (Duncan and Duncan (1955); White (1986)) using the formula $D_a = |s_{pa}/s_a - (1-s_{pa})/(1-s_a)|$, where s_a and s_{pa} are the share of Muslim electorate in AC a and in pin-code p in AC a, respectively. We identify the ACs with higher than median index as the ones with spatially concentrated Muslims. The result in column (6) shows that the high concentration ACs primarily drive the main effect, suggesting protest coordination as an important service provided by the legislators.

Columns (7) and (8) examine whether legislator characteristics – specifically experience and seniority – affect protest mobilization. We find no significant interaction effects with either incumbency status or legislator age (our proxy for seniority). This suggests that the coordination role played by Muslim representatives does not primarily depend on their political experience or seniority, but rather on their identity as representatives of the affected minority group.

7 Conclusion

This is the first paper to argue and empirically establish that political representation can be complementary to protests. This stands in contrast to the literature that has primarily highlighted the substitution effect of political representation on protests, as exemplified in the prominent democratization theories. We document this result in the context of India that enacted the Citizenship Amendment Act in 2019 putting the citizenship rights of Muslims at risk. We show using close election regression discontinuity design that electing a Muslim state legislator significantly increased probability of a CAA protest that followed, even though other non-CAA protest probability did not change. The result is not driven by party affiliation or incumbency of the legislator, and is robust to alternative datasets and specifications.

We argue that complementarity can arise in a context where political representatives are not able to directly shape decision-making, a concern which may get heightened during a potential disenfranchisement episode. In our context, Muslim legislators had two possible actions faced with the CAA legislation. Either directly communicate with the state government to resist its implementation (the substitution motive), or help facilitate protests as a way to convince the state government about the disaffection with the law (the complementarity motive). Their ability to do the former would be greater if they are larger in number in a state, and even more so if they are in the ruling party or coalition. Consistent with this argument, we show that the treatment effect is significantly lower in states with higher share of Muslim legislators, especially when they are in the ruling coalition. Since Muslim representatives constitute a small share of the state legislature in most states and majority of them were in the opposition, their ability to negotiate with the state executive was limited. This explains the protest facilitating role played by the Muslim representatives.

Threat to citizenship rights is an increasingly common phenomenon in the modern global politics. Can political representatives mount a direct challenge such unwelcome policy through institutional mechanisms? The results of our paper indicates that they may in fact activate the emphde jure power of citizens through protest mobilization as an effective strategy of resistance.

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Appendix

A Additional Figures and Tables

Table A1—Balance Table

	(1) Electors	(2) #Cand	(3) Turnout	(4) Female share	(5) Avg. Age	(6) ENOP	(7) Muslim share
Muslim Winner	-38.17	-1.27	0.03	-0.02	1.57	-0.22	0.02
	(31.69)	(1.22)	(0.03)	(0.02)	(1.26)	(0.24)	(0.04)
Mean dep. var.	222.25	10.94	0.73	0.07	46.73	3.20	0.26
Observations	300	300	293	300	271	257	285
	(8) SC share	(9) 0-6 y.o. share	(10) Sex ratio	(11) Primary edu share	(12) Emp. share	(13) Land ownership	(14) Irrig. share
Muslim Winner	0.01	-0.03	0.01	0.03	0.02	-0.03	-0.07
	(0.02)	(0.03)	(0.04)	(0.06)	(0.07)	(0.08)	(0.09)
Mean dep. var.	0.03	0.12	0.97	0.63	0.82	0.43	0.59
Observations	157	157	157	157	300	134	134
Bandwidth (h^*)	0.118	0.118	0.118	0.118	0.118	0.118	0.118
Polynomial order	1	1	1	1	1	1	1

Notes: The table reports regression discontinuity estimate using Muslim margin of victory in Assembly Constituencies (ACs) of Indian states as the running variables. The Muslim margin of victory is calculated for the last election prior to the 2020 CAA protests. The dependent variables are electoral and pre-existing characteristics of ACs. The non-electoral dependent variables, except AC Muslim share, are sourced from SHRUG data. AC Muslim share is calculated from a random sample of voter names across ACs, using a religion prediction ML algorithm. All columns use the specification and CCT optimal bandwidth used for column (1) of Table 1. Robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2—Robustness - Dropping Major States

	Dep. var.: Any CAA Protest					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dropping Northern and Eastern States					
	Full sample	UP	WB	AS	BH	UP + WB + AS + BH
Muslim Winner	0.18**	0.17**	0.21***	0.18***	0.16**	0.22***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)
Observations	300	237	259	281	274	151
	Panel B: Dropping Southern and Western States					
		MH	KT	AP	KR	MH + KT + AP + KR
Muslim Winner		0.18**	0.18**	0.19***	0.19**	0.21**
		(0.08)	(0.07)	(0.07)	(0.09)	(0.09)
Observations		284	291	295	284	254
Bandwidth (h^*)	0.118	0.118	0.118	0.118	0.118	0.118
Polynomial order	1	1	1	1	1	1
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports regression discontinuity estimate using Muslim margin of victory in Assembly Constituencies (ACs) of Indian states as the running variables. The Muslim margin of victory is calculated for the last election prior to the 2020 CAA protests. The dependent variable is a dummy that takes value one if any CAA protest happened in the AC and is zero otherwise. Column 1 report the results for full sample, while the subsequent columns drop ACs in Uttar Pradesh (Column 2), West Bengal (Column 3), Assam (Column 4), Bihar (Column 5) and all the four states together (Column 6). All specifications have state fixed effects. All columns use the CCT optimal bandwidth. Robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1