Supplemental Information:
Elite Responses to Ethnic Diversity and Interethnic Contact

Contents

SI.1: Survey Questions

- Pre-Survey Questions:
  1. Name of corporator.
  2. Female: 1-Female, 0-Male.
  3. Caste Reservation: 1-Constituency is caste reserved, 0-Otherwise.
  4. State: Gujarat, Karnataka, Kerala, Uttar Pradesh, West Bengal.
  5. Corporation: Name of corporation.
  6. Constituency: A description of the constituency the corporator represents (usually a ward number).
  7. Political Party: Name of corporator's political party. Recoded into BJP: 1-If party is BJP, 0-Otherwise and INC: 1-If party is Indian National Congress, 0-Otherwise.
  8. Committees: List of committees the corporator serves on.
  9. Number Committees On: Total number of committees the corporator serves on.
  10. Times Elected: Number of times elected to the corporation. Recoded into number of years in office and dichotomized for those serving more than 5 years (one term).
  11. Corporator phone number (redacted).
  12. Committee Asked About: Name of committee each corporator was asked about.
  13. Committee Diversity: Herfindahl-Hirschman index with six caste categories (Brahmin, OF, SC, ST, OBC, Other Religion) coded using the method described below for each committee.
- Pre-Treatment Questions:
  14. UniqueIDFinal: Unique respondent ID.
  15. Contact: Using the committee asked about, a list of up to four corporators was selected for inclusion in this survey question. A respondent was asked about four corporators if the committee had five or more members; a respondent was asked about the entire committee if there were fewer than five members. Block randomization by caste reserved seat was used to select the four corporators to ask about in committees with more than five members. This helped ensure that each respondent was asked about at least one non-coethnic committee member.

This question was repeated up to four times, once for each of the selected committee members: "I am going to ask you how frequently you talk to other members on the {name of committee asked about} committee. Please answer on a scale from 1 meaning you never talk to this person to 5 meaning you talk to this person every day. How frequently do you talk to {name of committee member}?"

Each committee member asked about was then caste coded, and coethnic committee members were excluded. Among non-coethnic committee members, I added up the reported frequency of contact and divided by the total number of committee members asked about. This is the main measure of contact used. I also measured contact between just forward and backward castes where Brahmin and OF are forward castes and all other categories are backward castes.

16. "Would you say that your interactions with other committee members are mostly cooperative, mostly conflictual, or some of both?" (Record response where 0-mostly conflictual, 1-some of both, 2-mostly cooperative).

- Treatment Administration:
  - Control: "As you know, committees often contain different types of members. Committee members often have very different viewpoints and feel that different policies are important."
  - Treatment: "As you know, committees often contain members belonging to different caste and religious groups. Because of caste and religious differences, committee members often have very different viewpoints and feel that different policies are important."
  - Recorded as 1-Treatment administered, 0-Control administered. Block randomized by caste reservation. Enumerators were instructed to read the text slowly and clearly and to wait a few seconds after reading it. Since this was a phone survey, we can ensure that the control or treatment were fully administered.
- Dependent Variables:

17. Spend Wisely: "Suppose a member of the {the name of the committee recorded in question 4} committee receives money to work on a policy of great importance to you. How likely is it that they spend the money wisely?" (Record response where 1-not likely to 5-very likely).
18. Opinions: "In general, how likely are you to take the opinions of other member of the committee into account when you make decisions?" (Record response where 1-not likely to 5-very likely).
19. Valid Concerns: "Consider a situation in which a member of the committee who has a different background and experiences from you disagrees with you. How likely are their concerns to be valid?" (Record response where 1-not likely to 5-very likely).
20. One Group: "To what extent do you think of the committee as one group as opposed to a collection of individuals with different experiences?" (Record response where 1-collection of individuals and 5-one group). Note that the initial scale was 0-collection of individuals and 1-one group, but that the survey was implemented with a 1 to 5 scale.
21. Enthusiastic: "How enthusiastic do you feel when working with others on the {the name of the committee being asked about} committee?" (Record response where 1-not at all to 5-very).
22. Angry: "How angry do you feel when working with others on the {the name of the committee being asked about} committee?" (Record response where 1-not at all to 5-very).
23. Hopeful: "How hopeful do you feel when working with others on the {the name of the committee being asked about} committee?" (Record response where 1-not at all to 5-very).
24. Resentful: "How resentful do you feel when working with others on the {the name of the committee being asked about} committee?" (Record response where 1-not at all to 5-very).
25. Donation: "We would like to give some money to an Indian NGO to thank you for your taking this survey. Would you like us to give to a charity that supports the betterment of lower castes or a charity that helps with disaster aid?" (Record response where 0-disaster relief and 1-caste betterment). Note that I donated to the India Development and Relief Fund and Dalit Solidarity respectively.

26. Caste Trust: "I have just a few more questions for you before we finish. On a scale from 1 to 5 where 1 means very much disagree and 5 means very much agree, how much would you agree with the following statements?" "Members of the {the name of the committee asked about} committee who are from different caste or religious backgrounds keep their word and do what is agreed on." (Record response where 1- very much disagree to 5- very much agree).
27. Neighbor: "You would be uncomfortable if someone who was a member of a different caste or religious group moved in next door to you." (Record response where 1- very much disagree to 5- very much agree). Reverse coded.
28. Talk: "You would be happy to talk to someone who was a member of a different caste or religious group." (Record response where 1- very much disagree to 5- very much agree).

- Post-Treatment Demographics:

29. Age: "What is your age?" (Enter age in years).
30. Social Media: "Are you never, sometimes, or frequently professionally active on social media?" (0-never, 1-sometimes, 2-frequently). Recoded where 1-Sometimes or frequently and 0-Never.
31. Education: "How many standards or years of education have you completed?" (Code response in years where: no formal education-0, 1st class-1, 5th class-5, Secondary-10, Bachelors-15, Above Bachelors-16). Recoded where 1-Completed Bachelors and 0-Otherwise.
32. Self-Reported Caste: "Are you: Brahmin, General/Forward, Schedule Caste, Schedule Tribe, Other Backward Class, or non-Hindu/other religion?" (Code response as: Brahmin, General/Forward, Schedule Caste, Schedule Tribe, Other Backward Class, or non-Hindu/other religion).
33. Occupation: "What was your primary occupation before being elected to the municipal corporation?" (Record response).

- Survey Information:

34. Times Called: Number of times the respondent was called before responding to the survey.
35. Interview Language: Language of the interview.
36. Interviewer: Name of the survey enumerator.
37. Date: Date the interview was conducted.

Table SI.1.1 lists descriptive statistics for key independent and dependent variables at the individual level. We might be concerned here with floor or ceiling effects. Indeed, the mean values of most dependent variables are in the "agree" range. This is likely because of social desirability bias in the survey. However, there is substantial variation across dependent variables, and a significant number of respondents chose 3 or less on the 1 to 5 scale.

To what extent are socially desirable responses a problem? First, respondents are likely to provide socially desirable responses to all questions including the frequency of contact, outgroup views, and ethnic self-identification. The independent variables of interest are measured indirectly, meaning that the respondent would have to know more information about the survey than is available to them in order to provide a socially desirable response. For the measures of outgroup views, initial questions start out without explicitly mentioning ethnicity in order to reduce socially desirable responses. When ethnicity is mentioned, all respondents are likely to respond in similar socially desirable ways, not somehow conditioning their socially desirable responses based on their measures of inerethnic contact and committee diversity. Finally, we know from the mixed nature of the results — views of committee members slightly worsen whereas outgroup attitudes improve in response to increased contact — that social desirability is not a major concern or else we would be quite unlikely to see the combination of these two results simultaneously.

SI.2: Sampling Procedure and Treatment Assignment

This study relies on data from data from municipal corporations in five Indian states. In this section, I explain the process for selecting the states from which to collect data, the data collection process, the sampling process, and the treatment assignment.

Table SI.1.1: Individual Level Descriptive Statistics

Variable	Min	Max	SD	Mean	Median
Diversity	0.00	0.79	0.15	0.59	0.64
Pct. Not Forward	0.00	1.00	0.26	0.50	0.45
Contact	0.00	1.00	0.15	0.62	0.60
Contact (Forward/Backward)	0.00	1.00	0.18	0.62	0.60
Spend Wisely	1.00	5.00	1.03	4.12	4.00
Opinions	1.00	5.00	0.88	4.31	5.00
Valid Concerns	1.00	5.00	1.32	3.55	4.00
One Group	1.00	5.00	0.87	4.17	4.00
Caste Trust	1.00	5.00	0.93	3.68	4.00
Talk	1.00	5.00	0.90	4.10	4.00
Neighbor	1.00	5.00	1.24	3.66	4.00
Committee Positive Interaction	0.00	1.00	0.38	0.82	1.00
Enthusiastic	1.00	5.00	0.75	4.43	5.00
Angry	1.00	5.00	1.04	1.88	2.00
Hopeful	1.00	5.00	1.44	3.49	4.00
Resentful	1.00	5.00	1.02	1.84	2.00
Donation	0.00	1.00	0.31	0.11	0.00
Age	24.00	70.00	7.72	47.38	48.00
Female	0.00	1.00	0.50	0.44	0.00
Year Elected	1974.00	2019.00	5.73	2012.17	2015.00
Caste Reservation	0.00	1.00	0.40	0.20	0.00
Brahmin	0.00	1.00	0.29	0.09	0.00
OF	0.00	1.00	0.49	0.42	0.00
OBC	0.00	1.00	0.43	0.24	0.00
SC	0.00	1.00	0.30	0.10	0.00
ST	0.00	1.00	0.16	0.03	0.00
Other Religion	0.00	1.00	0.33	0.12	0.00
BJP	0.00	1.00	0.50	0.55	1.00
INC	0.00	1.00	0.36	0.15	0.00
Bachelors Degree	0.00	1.00	0.50	0.55	1.00
Multi-Term	0.00	1.00	0.47	0.33	0.00
Social Media Active	0.00	1.00	0.50	0.43	0.00
Called Three Times	0.00	1.00	0.48	0.36	0.00

The goal in selecting states in which to conduct the survey was to maximize the number of municipal corporations and municipal corporation committees that I could survey. To achieve this goal, I began by accessing and reading the municipal corporation acts for each of the 27 Indian states. In reading these documents, I determined basic information about the composition of the municipal corporation and the number of committees. States set the structure of their corporations to either include only ward committees or to include one or more general (sometimes called standing) committees usually with ward committees. I excluded all states that only had ward committees with no general committees. I then attempted to calculate the number of committees and the number of councillors on each committee to get an estimate of total sample size. I based this estimate off of available committee lists on the websites of as many municipal corporations as I could access. Most municipal corporations do not list committee membership on their websites, so this is a biased estimate.

As a result of this process, eight states emerged where I estimated that there were many committees with many members on each committee. These states were: Gujarat, Karnataka, Kerala, Orissa, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. Tamil Nadu was excluded because no elected councillors existed at the time of the survey; elections had been postponed for many years and bureaucrats ran the government. I also excluded Orissa and Rajasthan because they had fewer municipal corporations than other states and because the remaining five states provided good geographic variance, variance in caste salience, and variance in municipal corporation authority.

These five states (Gujarat, Karnataka, Kerala, Uttar Pradesh, and West Bengal) collectively have 55 municipal corporations. The survey firm Morsel collected contact information for councillors in these 55 corporations from November 2, 2019 through March 27, 2020. The data collection process worked as follows:

- File a Right to Information Act request with each municipal corporation for the list of councillors and their phone numbers.
- Wait one month for the reply to the RTI. If no response, call the corporation secretary and inquire about the RTI status. File a second RTI if necessary.
- If a corporation still did not reply to the RTI (few did), send a trained survey enumerator to each corporation to attempt to collect the information in person. This procedure typically required several visits to the corporation offices and a lot of persistence.

After going through this procedure, Morsel obtained complete contact information for 25 of the 55 municipal corporations. Included corporations: Agra, Aligarh, Allahbad, Ayodhya, Bariely, Gorakhpur, Jhansi, Kanpur, Morabad, Saharanpur, Varanasi, Siliguri, Bangalore, Mysore, Ahmedabad, Surat, Vadodra, Rajkot, Bhavnagar, Jamnagar, Kollam, Thrissur, Kochi, Kozhikode, and Thiruvananthapuram.

There were three reasons why Morsel was unable to obtain contact information for committee members in a municipal corporation:

- No Committee: Despite the state municipal corporation acts expressly dictating that each corporation contain a certain number of committees, 15 corporations lacked any committee. Hence, no contact information could be obtained. Faizabad, Lucknow, Meerut, Mathura, Shahjahanpur, Ghaziabad, English Bazar, Maheshtala, Barasat, Dum Dum, Baharampur, Mangaluru, Tumkuru, and Shivamogga.
- Not Available: In 9 corporations, data is theoretically available, but could not be collected. Part of the data collection occurred during the coronavirus pandemic. Though Morsel was able to complete contact information collection in most corporations before the March 24, 2020 Government of India lockdown, some corporations still had not responded by that date. For this reason, these corporations were necessarily excluded. Hubbali, Kalaburgi, Belagavi, Davangere, Ballari, Vijaypura, Junagdh, Gandhinagar, and Kannur.
- No Authority: Many corporations in West Bengal claimed that Morsel did not have proper authority to obtain contact information for municipal councillors and that permission was needed from the Chief Minister or litigation was required. Neither of these options were feasible. Kolkata, Asansol, Durgapur, Bidhannagar-Rajarhat, Serampore, Chandannagar, and Barrackpore.

Upon obtaining the names and phone numbers for each corporator, Morsel phoned each corporator and asked the pre-survey questions. This was done to ensure that the corporator had a working phone number and to collect information about corporators whose phone numbers did not work. For example, Morsel asked other corporators in the corporation to verify information about a corporator who could not be reached via phone.

As a result of this process, Morsel collected contact information for 872 corporators. I took this contact information and assigned Morsel to ask each corporator about a specific committee to which they were a member. There are 146 committees across the 25 municipal corporations. I only asked corporators about committees with at least three members, as two members constitute a pair, not a committee. In Uttar Pradesh (except Muradabad), Karnataka, Kerala, and West Bengal, each corporator belonged to only one committee, so I asked about that committee. In Gujarat, each corporator belonged to up to five committees. I assigned each corporator to a committee to maximize the number of committees I asked about in the survey.

I then prepared a call sheet for Morsel to use to complete the survey consisting of half of the total corporators. Corporators were block randomized into the call sheet based on whether the corporator's seat was reserved or not. The call sheet was then purely randomized. Morsel was instructed to survey each person on the call sheet so as not to only collect information from those who answered their phone the first time Morsel called. Indeed, respondents were called up to ten times in order to get them to complete the survey. After completing the call sheet, Morsel contacted 45 additional respondents from the other half of the total corporators, starting with those at the top of the list of remaining corporators.

Only 48 of 455 respondents contacted did not participate for a completion rate of 90%.[1] This completion rate is incredibly high, so there is no concern about selection bias for only surveying those available or willing to participate. Of those who refused, the most common reasons were not being interested or not having time.

SI.3: Randomization and Balance Checks

Table SI.3.1 shows a multinomial logistic regression model where the dependent variable is the treatment indicator used in the survey experiment. Age is the only variable that predicts assignment to the treatment, supporting the claim that the treatment was randomly assigned. The Wald Test assesses whether the covariates have more combined predictive power than a restricted model with just an intercept; it is not significant.

Table SI.3.2 displays mean values for treated and control units as well as a Welsh Two Sample t-test indicating whether the covariate individually predicts the treatment assignment. Only two individual covariates significantly predict treatment assignment. Thus, individual covariates were successfully randomized across the treatment and control conditions.

Table SI.3.3 displays the caste composition of different groups of corporators along with p-values that result from t-tests comparing the mean caste composition. The first column shows the caste composition of committee members whose names were selected for inclusion in one of the four survey questions asking survey respondents about their contact with committee members. The second column is the mean caste composition of survey respondents with p-values from a Welch two sample t-test following. Column four displays the mean caste composition of those individuals selected to be on the call sheet (i.e., survey respondents plus those selected to respond to the survey who refused to do so). Column six displays the mean caste composition of those individuals not selected to be on the call sheet. No t-tests produce statistically significant p-values. Therefore, we can be confident that the committee members whose names were selected for inclusion in one of the four survey questions asking survey respondents about their contact with committee members are not different from survey respondents and corporators within the selected corporations as a whole.

[1] Twenty-eight of the 45 respondents from the other half of the corporators responded; no data is recorded for the remaining 17 respondents.

Table SI.3.1: Randomization Check

	Dependent variable:
	Treated
Female	-0.112
	(0.227)
Age	0.037^{**}
	(0.015)
Social Media Active	0.393
	(0.237)
BA	-0.124
	(0.239)
Multi-Term	-0.291
	(0.245)
BJP	-0.611
	(0.355)
INC	-0.299
	(0.368)
Called Three Times	0.138
	(0.253)
Caste Reservation	-0.072
	(0.311)
Constant	-0.200
	(1.100)
Wald Test	1.30
Corporation Fixed Effects	✓
Note:	**p<0.05; ***p<0.01

Multinomial logistic regression.

Table SI.3.2: Individual Covariate Balance

	Mean 1	Mean 0	Estimate	Std. Error	p-value
Female	0.42	0.46	-0.04	0.05	0.48
Age	48.46	46.32	0.01	0.00	0.01
Social Media	0.48	0.38	0.10	0.05	0.06
Education	0.55	0.55	0.00	0.05	0.99
Years Served	0.31	0.36	-0.07	0.05	0.22
BJP	0.49	0.62	-0.14	0.05	0.01
INC	0.16	0.15	0.02	0.07	0.75
Times Called	0.34	0.38	-0.05	0.05	0.34
Reserved	0.19	0.22	-0.05	0.06	0.42
Brahmin	0.08	0.11	-0.08	0.09	0.32
OF	0.40	0.43	-0.03	0.05	0.54
SC	0.09	0.10	-0.01	0.08	0.89
ST	0.03	0.03	-0.04	0.15	0.77
OBC	0.26	0.23	0.05	0.06	0.39
Other Religion	0.14	0.11	0.07	0.08	0.35

OLS regressions of each covariate on the specified attribute with standard errors and p-values. Mean 1 refers to when the specified attribute was 1, Mean 0 refers to when the specified attribute was 0. OLS p-values are equivalent to Welch Two Sample t-tests.

Table SI.3.3: Caste Composition of Sample

	Mean Asked About	Mean Respondents	p-value	Mean Called	p-value	Mean Not Called	p-value
Brahmin	0.09	0.09	0.93	0.09	0.68	0.08	0.54
OF	0.40	0.41	0.70	0.41	0.79	0.39	0.74
SC	0.10	0.09	0.95	0.10	0.73	0.09	0.56
ST	0.02	0.03	0.37	0.04	0.24	0.02	0.78
OBC	0.27	0.25	0.39	0.25	0.30	0.30	0.27
Other Religion	0.12	0.12	0.82	0.12	0.71	0.12	0.92

Caste composition of committee members whose names were selected for inclusion in one of the four survey questions asking survey respondents about their contact with committee members, survey respondents, individuals on the call sheet, and individuals not on the call sheet. p-values from Welch Two Sample t-tests.

SI.4: Affect Toward the Cabinet Classification

I use seven different methods for classifying affect toward the cabinet from the four emotion questions that appear post-treatment. According to Gubler and Karpowitz (2019), the minimum residual Bartlett method is the most accurate. Thus, the main text presents results from the minimum residual Bartlett method. I start by taking the four emotion questions and seeing how well they load on two two dimensions: one for pleasant (enthusiastic, hopeful) and one for unpleasant (angry, resentful) emotions. I generate bi-plots to show that the four emotion questions do load onto two dimensions. I then run the seven different types of factor analysis with two factors and compare the correlation between pleasant and unpleasant factors. These correlations are consistently above 0.80 between different factor analysis methods, indicating that all the methods are essentially identifying the same two underlying factors. Pseudo-correlations using Cramer's V (Table SI.4.1) are all above 0.80. I then plot the two factors and identify the four affective states — weak (neither pleasant nor unpleasant), mixed (both pleasant and unpleasant), pleasant, and unpleasant — by splitting axes at their zero lines. Next, I compare the affective state classification between different factor analysis methods. The majority of respondents' affective state classifications were consistent across all seven factor analysis methods. Finally, I create dichotomous dependent variables indicating that a respondent belonged to a given affective state.

Table SI.4.1: Cramer's V Correlation Between Categorical Variables

	Minres Reg	Minres Bartlett	Maxlik Reg	Maxlik Bartlett	PA Reg	PA Bartlett	PCA
Minres Reg	1.00	0.82	0.99	0.82	0.91	0.83	0.83
Minres Bartlett	0.82	1.00	0.82	1.00	0.89	0.98	0.86
Maxlik Reg	0.99	0.82	1.00	0.82	0.90	0.82	0.83
Maxlik Bartlett	0.82	1.00	0.82	1.00	0.89	0.98	0.86
PA Reg	0.91	0.89	0.90	0.89	1.00	0.90	0.84
PA Bartlett	0.83	0.98	0.82	0.98	0.90	1.00	0.84
PCA	0.83	0.86	0.83	0.86	0.84	0.84	1.00

Pseudo-correlation between seven affective state classifications.

I focus on affect toward the committee because I argue that affect toward the committee is an initial emotional response to increasing ethnic diversity or interethnic contact that may then have impacts on perceptions of the competence of the committee and outgroup attitudes. Outgroup attitudes may themselves be impacted by affect toward the outgroup. In other words, when perceptions of the competence of the committee improve, elites may develop positive feelings toward ethnic ougroups. These positive feelings are then what influences what we traditionally call outgroup attitudes (e.g., willingness to have an outgroup neighbor or to talk to an outgroup member). Affect is partially baked into these measures of outgroup attitudes because these questions assume that talking to an outgroup member or having an outgroup neighbor are items that elites support only when they have generated positive (or at least neutral) feelings about an ethnic outgroup. Elites gain no utility from talking to an outgroup member or having an outgroup neighbor beyond a potentially positive emotional response. Therefore, it could be interesting to explicitly evaluate affect toward outgroups as an intermediate step between perceiving that members of a committee are competent and improved outgroup attitudes. Slightly different outgroup attitudes questions may be required in order to more cleanly distinguish between affect toward outgroups and acts of outgroup tolerance.

SI.5: Committee Diversity and Contact Coding

The measures of committee diversity and contact used in this analysis rely on identifying the ethnicity of municipal corporators. The committee diversity measure uses ethnic group membership directly by aggregating ethnicity at the committee level. The contact measure captures contact by retaining only the frequency of contact with outgroup members and, thus, relies on successfully identifying members of the outgroup.

The first step is to decide on the appropriate ethnic categories used to categorize municipal corporators. In the United States, ethnic categorization has become relatively standardized because social and political ethnic categories tend to align. In India, no such consensus exists because caste groupings are socially constructed in different ways in the social and political sphere and across cities and states. Therefore, I need to be precise in my conceptualization of politically relevant caste groupings, as the categorization system I choose will necessarily impact the results I obtain.

I define ethnic categorization as the combination of caste and religion. The term "caste" traditionally refers to jatis or sub-jatis of which there are thousands of such groups. Much of the political conversation surrounding caste occurs at the varna level, where each varna comprises a large number of jatis. Castes are typically classified into one of four varnas as dictated by the Rig Veda: Brahmin, Kshatriya, Vaishya, and Shudra. Some individuals are termed Backward Classes and are granted special provisions — or reservations — by the government. Castes and tribes may petition the government to be included as a member of a Scheduled Caste (SC), Scheduled Tribe (ST), or Other Backward Class (OBC). Those not included in reservations are considered forward castes and are typically separated into Brahmins and other forward castes (OF).

I am interested in classifying individuals into salient, caste-based political groups that are relevant across Indian states. As such, my focus is on caste categories, not on jatis or sub-jatis. I group individuals into six caste categories: Brahmin, OF, SC, ST, OBC, and Other Religion (Muslim, Christian, Sikh, et. cetera). These categories represent the most politically salient ethnic distinctions that are relevant across Indian states. Political representation of SCs, STs, and OBCs in legislatures and cabinets is an ongoing topic of conversation throughout India. The distinction between Brahmins and all other forward caste members reflects the traditional predominance of Brahmins in politics and the low salience of the other varnas with respect to one another.[2]

Ethnicity coding is an incredibly complex topic, and there is no method that guarantees accuracy. There are two existing approaches: name classification and archival research.

Name classification involves making an educated guess about caste or religious membership based on the corporator's name. The basic intuition is that names have been historically linked to particular caste categories such that hearing a given name will trigger an association with a caste category (Banerjee et al., 2009; Jayaraman, 2005). Experts (Mateos, Webber and Longley, 2007), online workers on crowdsourcing sites (Shah and Davis, 2017), and many different algorithms can be used to classify names. Algorithmic classification is becoming an increasingly popular way to code caste, and the typical algorithmic method uses training data from matrimonial website profiles (Chen, Chittoor and Vissa, 2015; Vissa, 2011).

An alternative to name classification is to conduct archival research. Archival research entails trying to find caste information about specific individuals, not just those who happen to share a person's name (Narain and Sharma, 1972). As such, if we are trying to classify Indian Prime Minister Narendra Modi, we would need to find information stating Modi's caste category; we would not rely on any signal that the surname Modi provided or our knowledge of the caste category of other people named Narendra Modi.

Finally, corporators could be asked to reveal their caste on a survey. Though caste membership is a common political topic, asking for caste identification on a survey is relatively rare.

Accuracy is an important question to consider when employing any of these methods. One concern is social desirability bias. Social desirability bias can occur whenever individuals are asked to self-report their

[2] Another reason for adopting these six categories is replicability and comparability; the largest social survey in India (Desai and Vanneman, 2015) uses these categories.

caste or religious membership. Matrimonial website data severely under-reports individuals from lower castes likely due in part to users mis-representing or hiding their caste membership (Rajadesingan, Mahalingam and Jurgens, 2019).

Similarly, ethnic categorization is a contentious topic, and asking individuals to self-identify may produce socially desirable responses. The ethnic categorization question on this survey experiment appears at the very end to eliminate any treatment contamination. As a result, respondents have been asked a number of questions about inter-ethnic relations including a donation question that explicitly asks respondents to donate to backward caste welfare. Socially desirable responses in this context are both those wherein a backward caste respondent affiliates with a forward caste and where a forward caste respondent affiliates with a backward caste. In the former case, the respondent is cued on caste and does not wish to reveal her backward caste status and, therefore, claims forward caste membership. However, in the latter case, the respondent learns from the content of the survey that the questions are directed toward backward caste welfare and identifies as that group because they believe that is what the survey enumerator wants.

Second, there are often differences between ways in which caste or religion are employed. Caste (and to a lesser extent religious) categories can be constructed in at least four ways: self-identification, government identification, political construction, and social construction. Self-identification refers to how individuals classify themselves. These self-categorizations may change depending on the context in which the question is asked or based on events and life experiences. Government identification in India refers mostly to caste categories that need to register in order to obtain certain government benefits. Political construction is based on how caste and caste identity is portrayed in politics. A political party can target a certain group of people and assert that they are part of a shared caste category, for example. Finally, social caste relations are based on relationships among members of the public and the caste categories people perceive each other belonging to. These four ways that caste is employed often align, but sometimes diverge.

For the purposes of this study, I am most interested in how others perceive someone's caste or religious category, not necessarily how people self-identify. Outward perceptions of ethnicity are wrapped up in government, political, and social conceptions of caste and religion. For example, if someone holds a reserved seat in the corporation, then I argue that this person will be outwardly perceived as belonging to the caste category associated with that reserved seat, even if the person self-identifies differently. Similarly, cues about a person's caste categorization — like their name or what local people think their caste categorization is — are more influential for how others perceive them and their caste compared to self-identification.

Classification Approach

To classify the caste of these corporators, I first cross-reference corporator names with official Indian election results and code all corporators who won seats reserved for SCs, STs, or OBCs. The caste coding for these individuals is exact: we know for certain that a corporator is a SC, ST, or OBC if they were elected in such a constituency (even if they may self-identify otherwise).

Of course not all individuals who are SCs, STs, or OBCs run in reserved constituencies, and public records do little to help classify individuals into other ethnic categories. Absent a coding based on electoral lists, I moved to expert name classification. Local knowledge is key to successful name-caste or religious coding: I employed a specially trained native Indian coder to perform the coding and provided detailed instructions about how the coding should proceed. First, I provided the coder with a list of all unique surnames that remained to be coded in the dataset. The coder was instructed to only classify surnames where the surname clearly indicated caste or religious affiliation. Each name coding was accompanied by a confidence level of high (90%+ confident), medium (75%-90% confident), or low (less than 75% confident). I then manually reviewed each surname coding and compared it to both local knowledge and archival research conducted on approximately 5% of the sample. I deemed a surname coding accurate when it was coded with either high or medium confidence and passed the manual review.

After completing surname classification, I took all remaining names and provided the coder with the full name of the corporator, their state of residence, gender, and the name of the corporation. This information helped her classify names that often belong to different castes depending on state. It also enabled her to perform basic Internet research on the history of certain surnames similar to Damaraju and Makhija (2018)'s approach. Again, the coder provided confidence levels for her coding and I conducted a spot check of 5% of the sample. All names not classified with at least a medium level of confidence were left for more intensive review.

Remaining surnames were subjected to a more intensive evaluation of archival records.[3] First, additional Internet research was performed in order to try to find available caste or religious information about specific corporators. If this failed, an expert coder contacted journalists and local sources in the corporator's municipal corporation to obtain an exact coding.

This classification approach is used in the main analysis.

Self-Coding Classification

In addition to the classification approach discussed above, corporators that participated in the survey experiment were asked to self-identify their ethnic category. This question was necessarily included at the very end of the survey as a post-treatment demographic variable.

Apart from the issues with ethnic self-identification described above, the post-treatment nature of this question meant that respondents were fully aware that the survey was about ethnic relationships and even, based on the donation question, that the survey was asking about their experiences with lower caste individuals. Thus, social desirability bias is likely extremely high in this situation.

Further, I would highlight that the survey took place on the phone which is more impersonal than a face-to-face interview, so corporators are freer to self-identify with whatever ethnicity they so choose without fear of retribution.

As a robustness check, I substituted the available ethnic self-identification for the main classification method. The particular method used did not substantively impact the results.

Calculating Diversity

The diversity measure is the Herfindahl-Hirschman index, written as $1 - \sum_{i=1}^{p} x_i^2$ where x_i represents the percentage of each of the ethnic categories present in a given committee and p is the number of caste categories (6) (Jensenius and Suryanarayan, 2015; Lancee and Dronkers, 2011; Tallman and Li, 1996).[1] If one caste category dominates the committee, the index is low (close to 0); if groups are relatively equal in size, the index is high (close to 1) (Harrison and Klein, 2007).

The correlation between coded classification and self-reported classification exceeds 0.75 for both diversity and contact measures, likely explaining why there are consistent results across measures.

Beyond correlating these two measures, I wanted to investigate specific discrepancies that occurred in the ethnicity coding to better understand why these discrepancies took place. A discrepancy is any difference in caste categorization between self-reported classification and coded classification. Table SI.5.1 shows the overall number of corporators coded in a given state and the number of discrepancies identified in a given state. There are slight differences, but in general, the percentage of discrepancies is in line with the percentage of corporators in each state.

Table SI.5.1: Overall and Discrepancies by State

Method	Overall (Pct.)	Discrepancies (Pct.)
Gujarat	323 (0.37)	116 (0.46)
Karnataka	85 (0.10)	17 (0.07)
Kerala	317 (0.36)	91 (0.36)
Uttar Pradesh	114 (0.13)	23 (0.09)
West Bengal	33 (0.04)	6 (0.03)

Table SI.5.2 shows the overall number of corporators coded with a given method and the number of discrepancies identified with this method. As is evident from the table, discrepancies do not occur based on the coding method. What is also interesting to note is that a quarter of the discrepancies that occurred resulted from corporator names coded using reservation status. There is almost no error in coding reservation

[3] In previous work, I have used the *People of India Project* (Singh, 1996) book to provide further surname classification, but this book has proved to have limited use.

status — either a seat is reserved for a particular caste or it is not. So these discrepancies are all individuals whose self-identification contradicts publicly available caste information. Additionally, archival work was just as precise. Experts used local sources to code ethnicity and described both the method used and why each coding was appropriate. Yet, a fifth of the discrepancies came from archival coded names. These two facts reinforce some of the potential issues with coding ethnicity using self-identification in survey responses. Neither ethnic coding method produces "wrong" results, but self-identification may not match the public perceptions of ethnicity that are important for characterizing committee diversity and contact.

Table SI.5.2: Overall and Discrepancies by Coding Type

Method	Overall (Pct.)	Discrepancies (Pct.)
Reservation	188 (0.22)	61 (0.24)
Surname	323 (0.37)	96 (0.38)
Full Name	172 (0.20)	45 (0.18)
Archival	179 (0.21)	47 (0.19)
Guess	10 (0.01)	4 (0.02)

With this in mind, I move to discussing the specific discrepancies. For each discrepancy, I first consulted with experts about the specific discrepancy and why it might be occurring. Second, I conducted archival research on ethnic categorization in each state to determine the likelihood of this discrepancy occurring. The goal was to provide some rationale for why each discrepancy might exist. I coded each discrepancy on a two point scale: 1 indicated that there was no reason to doubt the combined expert and archival ethnicity coding method, whereas 0 indicated that the accuracy of the coding method was in question. Based on these criteria, a discrepancy was coded "0" when the difference between the ethnicity coding and self-identification was not plausible or when the self-identification method was most likely correct. When the discrepancy made sense or the ethnicity coding method was most likely correct, the discrepancy was coded as "1."

Starting in Gujarat, of the 116 discrepancies, 100 were coded as 1 and 16 were coded as 0, meaning that 86% of the ethnicity codings in Gujarat made sense. Most of the discrepancies that were coded as "1" were the result of corporators who were coded as OF claiming to be SC, ST, or OBC. There are widespread movements occurring in Gujarat to redefine OF as a backward caste in order to obtain reservations. On the other hand, there is still a stigma associated with claiming to be a member of a reserved caste category, so a number of SC, ST, or OBC members may be claiming to be OF for this reason.

Of the 17 discrepancies in Karnataka, 15 were coded as 1 and 2 were coded as 0. That is, 88% of Karnataka ethnicity codings made sense and were likely correct after further investigation. Most discrepancies in Karnataka occurred in reserved constituencies, where OBCs tended to self-report that they were OF. This is quite a common type of discrepancy which indicates an unwillingness to reveal ones' actual ethnic category either because of social desirability or potential discrimination.

Moving to Kerala, of the 91 discrepancies 86 were coded as 1 and 5 were coded as 0. Hence, 95% of Kerala ethnicity codings made sense and were likely correct after further investigation. An investigation of the 86 names where ethnicity coding was likely correct revealed several patterns. First, many corporators were ethnicity coded as a backward caste, but self-reported belonging to OF. This is again due to an unwillingness to reveal their actual ethnic category and confusion over the reservations system in Kerala. Toward the latter point, a number of jatis receive reservations, but consider themselves to be OF. Additionally, a large number of corporators self-reported belonging to OF when they were categorized as other religion. This is because Muslims and Christians often place themselves into a caste category (usually OF) instead of identifying only with their religion.

In Uttar Pradesh, of the 23 discrepancies, 20 were coded as 1 and 3 as 0. This represents 87% of ethnicity codings in Uttar Pradesh that made sense and were likely correct after further investigation. The discrepancies that were likely correct were mostly individuals categorized as OF who identified as a backward caste. Recent BJP actions in Uttar Pradesh have sought to include new groups in the OBC list and to move OBCs to the SC reservation list, meaning that there are incentives for forward caste members to self-identify as backward castes.

Finally, of the 6 discrepancies in West Bengal, 4 were coded as 1 and 2 as 0. This is a relatively low percentage of discrepancies that made sense and were likely correct (67%), but there are few cases to examine.

All told, 225 of the 253 discrepancies (89%) could be explained and justified. 28 discrepancies (11%) were most likely errors in ethnicity coding. Most of the discrepancies that could be justified resulted from differences in the ways in which each coding procedure conceptualized caste and caste identity. Self-identification allowed respondents to profess the caste identity that they felt connected to, regardless of whether it matched their reservation status or the way they are treated in society. Caste groups trying to redefine themselves can do so in the self-identification measure, whereas the caste coding measure attempts to classify individuals based on the prevailing political understanding of their caste. As shown below, robustness checks using either measure do not influence the results. In the main text, I prioritize ethnicity coding over self-identification because the procedure used to arrive at the ethnicity coding is consistent, and ethnicity coding better reflects political realities of how diversity and contact are viewed within a state.

SI.6: Results and Robustness Checks

Table SI.6.1 displays regression results for the treatment, alongside diversity and contact, whereas Table SI.6.2 displays ordinal multilevel model results for these same variables. Since the none of the hypotheses are supported, p-value corrections for multiple comparisons are not particularly informative.

I conducted numerous robustness checks, only a subset of which are shown here to make the length of this document reasonable. I start by measuring diversity as the Percent Not Forward and contact between only forward and backward castes (Table SI.6.3). I then measure ethnicity using self-reported information where available (Table SI.6.4). Table SI.6.5 displays regression results with state instead of corporation fixed effects. Table SI.6.6 displays regression results including an additional variable, *Crime*, that is the logged total crimes committed against SCs and STs in 2017 as reported by the National Crime Records Bureau for a given corporation. Note that the crime figures for Siliguri include both the Darjeeling and Jalpaiguri districts, since Siliguri is located partly in both districts. To examine heterogeneous treatment effects, I restrict the analysis to only forward caste respondents to examine whether the effects depend on the caste category of the respondent. Table SI.6.7 displays the results. Finally, I ran models interacting the treatment with numerical diversity; there are no significant interaction effects.

Table SI.6.1: Main Text Results

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	−0.027	−0.016	0.005	0.039	−0.021	0.031	−0.023	0.024	0.017	0.054	0.062***	0.011
	(0.047)	(0.042)	(0.045)	(0.054)	(0.038)	(0.026)	(0.034)	(0.047)	(0.026)	(0.034)	(0.023)	(0.020)
Diversity	0.421	−0.371	0.167	−0.217	0.018	−0.022	−0.060	−0.010	0.026	0.003	−0.008	−0.132
	(0.232)	(0.243)	(0.171)	(0.257)	(0.095)	(0.076)	(0.170)	(0.232)	(0.133)	(0.156)	(0.075)	(0.190)
Contact	−0.010	0.108	0.416**	−0.515**	−0.105	−0.107	0.053	0.020	0.130	0.249**	0.227***	0.102
	(0.144)	(0.189)	(0.186)	(0.204)	(0.109)	(0.073)	(0.136)	(0.144)	(0.075)	(0.110)	(0.081)	(0.150)
Female	0.011	0.006	0.017	−0.033	−0.007	0.014	−0.022	0.002	0.008	0.002	0.020	0.013
	(0.048)	(0.049)	(0.037)	(0.040)	(0.024)	(0.026)	(0.039)	(0.048)	(0.021)	(0.026)	(0.029)	(0.019)
Age	0.004	0.003	0.003	−0.010***	−0.001	−0.002	−0.002	−0.002	0.0001	0.005**	0.003**	−0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
Social Media Active	0.164***	−0.014	0.030	−0.179***	−0.035	0.002	−0.085	−0.039	0.066**	0.057	0.095***	−0.006
	(0.064)	(0.033)	(0.042)	(0.049)	(0.024)	(0.025)	(0.047)	(0.064)	(0.029)	(0.047)	(0.025)	(0.046)
Bachelor's Degree	−0.034	0.061	0.051	−0.078	−0.040**	−0.049	−0.041	−0.049	0.018	0.088***	−0.003	0.033
	(0.043)	(0.057)	(0.036)	(0.052)	(0.019)	(0.027)	(0.038)	(0.043)	(0.014)	(0.033)	(0.020)	(0.025)
Multi-Term	−0.018	−0.014	0.021	0.011	−0.032	−0.023	−0.038	0.012	−0.028	−0.072***	−0.0004	0.060**
	(0.036)	(0.043)	(0.050)	(0.045)	(0.027)	(0.026)	(0.040)	(0.036)	(0.027)	(0.025)	(0.026)	(0.028)
BJP	−0.046	0.053	−0.052	0.045	−0.022	−0.0003	−0.028	0.016	−0.029	0.059	−0.069	0.055
	(0.056)	(0.065)	(0.038)	(0.047)	(0.048)	(0.032)	(0.055)	(0.056)	(0.032)	(0.048)	(0.037)	(0.042)
INC	−0.090	0.181**	−0.089	−0.001	−0.008	−0.077**	−0.013	−0.033	−0.049	0.085	−0.065	0.086
	(0.052)	(0.086)	(0.064)	(0.046)	(0.053)	(0.032)	(0.040)	(0.052)	(0.032)	(0.044)	(0.047)	(0.051)
Called Three Times	−0.109	0.052	0.023	0.034	0.013	−0.005	0.114***	−0.018	−0.046**	0.002	−0.025	−0.090**
	(0.071)	(0.045)	(0.046)	(0.036)	(0.031)	(0.027)	(0.036)	(0.071)	(0.022)	(0.035)	(0.030)	(0.041)
Caste Reservation	0.039	−0.004	−0.071	0.036	0.008	0.001	0.005	0.021	−0.044	0.074**	0.004	−0.044
	(0.063)	(0.044)	(0.061)	(0.049)	(0.044)	(0.023)	(0.071)	(0.063)	(0.044)	(0.034)	(0.035)	(0.022)
Constant	−0.161	0.278	−0.221	1.105***	0.723***	0.998***	0.606***	0.962***	0.708***	0.253	0.524***	0.228
	(0.203)	(0.187)	(0.196)	(0.310)	(0.108)	(0.082)	(0.156)	(0.203)	(0.141)	(0.131)	(0.056)	(0.144)
Observations	388	388	388	388	388	388	388	388	388	388	388	388
Note:												**p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, corporation fixed effects, and cluster robust standard errors.

Table SI.6.2: Main Text Results Multilevel Models

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(Intercept)	−2.90**	−1.85	−5.50***	4.55***								−2.80*
	(1.13)	(1.15)	(1.32)	(1.30)								(1.53)
Treated	−0.14	−0.14	0.10	0.28	−0.22	0.22	−0.11	0.19	0.14	0.31	0.58***	0.22
	(0.25)	(0.26)	(0.27)	(0.30)	(0.21)	(0.21)	(0.19)	(0.21)	(0.20)	(0.20)	(0.21)	(0.36)
Diversity	1.62	−1.53	1.32	−1.24	0.40	−0.47	−0.56	−0.33	0.04	0.70	0.09	−1.01
	(1.01)	(1.03)	(1.05)	(1.04)	(0.80)	(0.79)	(0.67)	(0.82)	(0.79)	(0.70)	(0.81)	(1.31)
Contact	−0.29	0.74	3.44***	−3.32***	−1.99***	−1.86**	0.66	−0.46	0.81	1.42**	1.68**	1.49
	(0.86)	(0.90)	(0.99)	(1.02)	(0.75)	(0.77)	(0.65)	(0.74)	(0.69)	(0.68)	(0.73)	(1.20)
Female	−0.04	0.08	0.16	−0.24	−0.09	0.03	−0.03	−0.00	0.01	0.02	0.26	0.17
	(0.26)	(0.26)	(0.26)	(0.30)	(0.21)	(0.21)	(0.19)	(0.22)	(0.20)	(0.20)	(0.21)	(0.36)
Age	0.01	0.02	0.03*	−0.07***	−0.02	−0.03**	−0.00	−0.03**	−0.00	0.03**	0.02*	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Social Media Active	0.88***	−0.01	0.21	−1.42***	−0.27	−0.02	−0.45**	−0.45**	0.68***	0.47**	0.88***	
	(0.27)	(0.27)	(0.27)	(0.36)	(0.21)	(0.22)	(0.20)	(0.22)	(0.21)	(0.21)	(0.22)	
Bachelor's Degree	−0.23	0.38	0.43	−0.58*	−0.50**	−0.73***	−0.33	−0.54**	0.25	0.44**	−0.05	
	(0.27)	(0.27)	(0.28)	(0.32)	(0.22)	(0.23)	(0.20)	(0.23)	(0.21)	(0.21)	(0.22)	
Multi-Term	0.05	−0.27	0.11	0.04	−0.13	−0.18	−0.30	0.22	−0.17	−0.52**	0.15	
	(0.27)	(0.28)	(0.27)	(0.33)	(0.22)	(0.22)	(0.20)	(0.22)	(0.22)	(0.21)	(0.22)	
BJP	0.52	−0.49	−0.78**	1.07**	0.07	0.77***	−0.36*	0.73**	0.04	0.43*	−0.24	0.75
	(0.37)	(0.39)	(0.35)	(0.44)	(0.30)	(0.29)	(0.22)	(0.33)	(0.30)	(0.25)	(0.33)	(0.54)
INC	−0.05	0.58	−0.76*	0.31	0.06	−0.25	−0.18	−0.08	−0.34	0.50*	−0.40	0.92
	(0.44)	(0.38)	(0.40)	(0.54)	(0.31)	(0.31)	(0.28)	(0.32)	(0.32)	(0.30)	(0.33)	(0.64)
Called Three Times	−0.40	0.05	−0.09	0.48	−0.01	0.13	0.42**	−0.00	−0.33	0.03	−0.13	
	(0.29)	(0.30)	(0.31)	(0.31)	(0.24)	(0.24)	(0.21)	(0.25)	(0.23)	(0.21)	(0.24)	
Caste Reservation	0.32	−0.03	−0.34	0.11	−0.12	0.05		−0.15	−0.45*	0.26	0.06	
	(0.31)	(0.34)	(0.35)	(0.37)	(0.27)	(0.27)		(0.29)	(0.28)	(0.25)	(0.28)	
Observations	388	388	388	388	388	388	388	388	388	388	388	388
Note:												**p<0.05; ***p<0.01

Ordered and logistic multilevel regression models with corporation random effects.

Table SI.6.3: Diversity and Contact Measured with Forward and Backward Castes

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	−0.024	−0.017	−0.009	0.050	−0.037	0.022	−0.015	0.039	0.006	0.038	0.054**	−0.001
	(0.047)	(0.043)	(0.044)	(0.059)	(0.044)	(0.023)	(0.041)	(0.047)	(0.028)	(0.038)	(0.024)	(0.025)
Contact	0.014	0.196	0.249	−0.458***	−0.169	−0.119**	−0.051	0.093	0.117**	0.222**	0.157**	0.150
	(0.158)	(0.194)	(0.168)	(0.146)	(0.094)	(0.060)	(0.123)	(0.158)	(0.057)	(0.102)	(0.076)	(0.144)
Pct. Not Forward	0.468**	−0.162	−0.146	−0.161	−0.141	−0.065	−0.096	0.009	−0.033	0.146	−0.016	0.009
	(0.232)	(0.170)	(0.098)	(0.200)	(0.122)	(0.079)	(0.086)	(0.232)	(0.077)	(0.117)	(0.110)	(0.179)
Female	0.043	0.046	−0.011	−0.078	−0.014	0.016	−0.043	−0.003	0.022	0.034	0.034	0.009
	(0.051)	(0.067)	(0.057)	(0.047)	(0.024)	(0.025)	(0.046)	(0.051)	(0.024)	(0.019)	(0.031)	(0.024)
Age	0.006**	0.003**	0.004	−0.013***	−0.0005	−0.003	−0.004	−0.002	0.001	0.007**	0.004***	−0.002
	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
Social Media Active	0.171***	−0.024	0.038	−0.184***	−0.040	0.002	−0.104**	−0.050	0.072**	0.046	0.090***	−0.013
	(0.065)	(0.035)	(0.046)	(0.051)	(0.028)	(0.025)	(0.050)	(0.065)	(0.031)	(0.049)	(0.029)	(0.048)
Bachelor's Degree	−0.023	0.048	0.055	−0.081	−0.027	−0.029	−0.017	−0.048	0.024	0.095***	0.003	0.040
	(0.050)	(0.061)	(0.049)	(0.056)	(0.021)	(0.028)	(0.040)	(0.050)	(0.018)	(0.036)	(0.025)	(0.029)
Multi-Term	−0.038	−0.023	0.048	0.013	−0.037	−0.040	−0.029	0.012	−0.031	−0.119***	−0.022	0.055**
	(0.035)	(0.045)	(0.055)	(0.046)	(0.032)	(0.025)	(0.038)	(0.035)	(0.030)	(0.033)	(0.028)	(0.025)
BJP	−0.038	−0.021	−0.046	0.105**	−0.003	−0.017	0.015	−0.016	−0.016	0.054	−0.092**	0.017
	(0.047)	(0.075)	(0.044)	(0.048)	(0.063)	(0.030)	(0.048)	(0.047)	(0.036)	(0.060)	(0.036)	(0.051)
INC	−0.087	0.097	−0.059	0.050	0.010	−0.094***	0.042	−0.075	−0.067**	0.093	−0.097	0.020
	(0.058)	(0.116)	(0.097)	(0.049)	(0.063)	(0.033)	(0.034)	(0.058)	(0.034)	(0.057)	(0.050)	(0.069)
Called Three Times	−0.096	0.067	0.031	−0.001	−0.006	−0.013	0.095**	−0.031	−0.035	0.045	−0.008	−0.078**
	(0.076)	(0.047)	(0.053)	(0.034)	(0.036)	(0.028)	(0.042)	(0.076)	(0.025)	(0.036)	(0.029)	(0.031)
Caste Reservation	0.033	−0.013	−0.024	0.004	0.008	−0.016	−0.010	0.012	−0.041	0.074	0.003	−0.064**
	(0.075)	(0.058)	(0.075)	(0.053)	(0.051)	(0.025)	(0.073)	(0.075)	(0.053)	(0.039)	(0.035)	(0.027)
Constant	−0.167	0.076	0.014	1.078***	0.798***	1.055***	0.707***	0.945***	0.702***	0.162	0.546***	0.107
	(0.190)	(0.168)	(0.166)	(0.249)	(0.128)	(0.078)	(0.182)	(0.190)	(0.107)	(0.116)	(0.094)	(0.094)
Observations	333	333	333	333	333	333	333	333	333	333	333	333
Note:												**p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, corporation fixed effects, and cluster robust standard errors.

Table SI.6.4: Self-Reported Contact

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	−0.025	−0.023	0.002	0.047	−0.014	0.037	−0.022	0.027	0.016	0.044	0.055**	0.008
	(0.039)	(0.037)	(0.042)	(0.051)	(0.041)	(0.025)	(0.034)	(0.039)	(0.024)	(0.033)	(0.022)	(0.022)
Self-Reported Contact	0.183	0.209	0.347**	−0.739***	−0.094	−0.019	−0.124	−0.077	0.188	0.341**	0.353***	0.093
	(0.166)	(0.160)	(0.156)	(0.223)	(0.106)	(0.077)	(0.115)	(0.166)	(0.096)	(0.158)	(0.069)	(0.171)
Self-Reported Diversity	0.015	0.209	−0.093	−0.131	−0.156	−0.171**	−0.134	−0.057	−0.002	0.066	−0.028	0.062
	(0.194)	(0.226)	(0.207)	(0.187)	(0.169)	(0.081)	(0.137)	(0.194)	(0.081)	(0.170)	(0.120)	(0.139)
Female	0.022	0.013	0.018	−0.052	−0.017	0.003	−0.030	−0.003	0.020	0.011	0.026	0.034
	(0.052)	(0.047)	(0.034)	(0.042)	(0.022)	(0.024)	(0.039)	(0.052)	(0.018)	(0.025)	(0.028)	(0.025)
Age	0.004	0.003	0.003	−0.011***	−0.002	−0.002	−0.002	−0.002	0.0002	0.006**	0.003***	−0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
Social Media Active	0.153**	−0.024	0.035	−0.165***	−0.040	0.006	−0.077	−0.035	0.061	0.052	0.083***	0.007
	(0.060)	(0.037)	(0.037)	(0.047)	(0.025)	(0.028)	(0.046)	(0.060)	(0.032)	(0.045)	(0.024)	(0.041)
Bachelor's Degree	−0.018	0.062	0.052	−0.095**	−0.034	−0.067**	−0.040	−0.048	0.019	0.088***	−0.002	0.015
	(0.035)	(0.053)	(0.034)	(0.049)	(0.020)	(0.028)	(0.038)	(0.035)	(0.014)	(0.031)	(0.018)	(0.027)
Multi-Term	−0.023	−0.015	0.038	−0.0004	−0.030	−0.027	−0.026	0.013	−0.020	−0.068***	0.005	0.055**
	(0.034)	(0.045)	(0.052)	(0.045)	(0.025)	(0.027)	(0.043)	(0.034)	(0.028)	(0.024)	(0.027)	(0.025)
BJP	−0.019	0.050	−0.060	0.029	−0.017	−0.005	−0.036	0.017	−0.035	0.060	−0.060	0.041
	(0.065)	(0.061)	(0.039)	(0.053)	(0.047)	(0.033)	(0.054)	(0.065)	(0.031)	(0.044)	(0.031)	(0.048)
INC	−0.080	0.170	−0.082	−0.009	0.006	−0.079***	−0.005	−0.032	−0.041	0.083	−0.066	0.059
	(0.049)	(0.087)	(0.064)	(0.047)	(0.052)	(0.028)	(0.040)	(0.049)	(0.028)	(0.043)	(0.046)	(0.057)
Called Three Times	−0.119	0.053	0.014	0.052	0.008	−0.001	0.112***	−0.013	−0.051**	−0.002	−0.026	−0.075
	(0.067)	(0.043)	(0.044)	(0.034)	(0.029)	(0.028)	(0.036)	(0.067)	(0.021)	(0.036)	(0.027)	(0.040)
Caste Reservation	0.055	−0.006	−0.062	0.014	0.005	−0.004	0.004	0.019	−0.044	0.082**	0.013	−0.044
	(0.061)	(0.042)	(0.051)	(0.043)	(0.044)	(0.023)	(0.070)	(0.061)	(0.046)	(0.034)	(0.033)	(0.025)
Constant	−0.027	−0.184	0.014	1.197***	0.867***	1.061***	0.764***	1.043***	0.697***	0.161	0.467***	0.070
	(0.206)	(0.167)	(0.190)	(0.255)	(0.121)	(0.083)	(0.192)	(0.206)	(0.099)	(0.146)	(0.081)	(0.161)
Observations	402	402	402	402	402	402	402	402	402	402	402	402

Note: **p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, corporation fixed effects, and cluster robust standard errors.

Table SI.6.5: State Fixed Effects

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	−0.023	−0.019	0.001	0.041**	−0.023	0.029**	−0.021	0.023	0.013	0.067	0.060***	0.023
	(0.042)	(0.039)	(0.028)	(0.017)	(0.014)	(0.013)	(0.018)	(0.042)	(0.013)	(0.039)	(0.022)	(0.031)
Diversity	0.376***	−0.294**	0.077	−0.159	0.066	0.016	−0.092	−0.021	−0.024	0.052	−0.006	−0.080
	(0.137)	(0.130)	(0.065)	(0.087)	(0.111)	(0.073)	(0.078)	(0.137)	(0.067)	(0.050)	(0.031)	(0.091)
Contact	−0.001	0.022	0.446**	−0.467***	−0.091	−0.059	0.075	0.022	0.147	0.297	0.223***	0.125
	(0.109)	(0.285)	(0.224)	(0.176)	(0.061)	(0.088)	(0.127)	(0.109)	(0.075)	(0.173)	(0.073)	(0.175)
Female	0.009	0.009	0.021	−0.039	−0.021	0.012	−0.023	0.004	0.011	−0.003	0.018	0.014
	(0.041)	(0.033)	(0.023)	(0.029)	(0.020)	(0.032)	(0.023)	(0.041)	(0.020)	(0.031)	(0.030)	(0.017)
Age	0.004	0.003	0.003	−0.010***	−0.002	−0.002	−0.001	−0.002	0.0004	0.005**	0.003***	−0.002
	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)
Social Media Active	0.166	−0.013	0.032	−0.185**	−0.045**	0.012	−0.085	−0.040	0.075**	0.069	0.097***	0.009
	(0.087)	(0.044)	(0.043)	(0.089)	(0.019)	(0.028)	(0.074)	(0.087)	(0.038)	(0.078)	(0.037)	(0.058)
Bachelor's Degree	−0.044	0.078	0.058	−0.092	−0.044***	−0.068***	−0.041	−0.049	0.018	0.078***	−0.007	0.020
	(0.040)	(0.081)	(0.046)	(0.098)	(0.014)	(0.011)	(0.028)	(0.040)	(0.011)	(0.013)	(0.029)	(0.018)
Multi-Term	−0.002	−0.029	0.020	0.012	−0.015	−0.029	−0.032	0.012	−0.037	−0.086***	−0.011	0.051
	(0.020)	(0.051)	(0.015)	(0.039)	(0.035)	(0.035)	(0.019)	(0.020)	(0.025)	(0.014)	(0.019)	(0.045)
BJP	−0.058	0.018	−0.021	0.062	−0.014	0.011	−0.020	0.025	−0.037***	0.047**	−0.042**	0.049
	(0.068)	(0.054)	(0.029)	(0.041)	(0.048)	(0.017)	(0.034)	(0.068)	(0.012)	(0.024)	(0.021)	(0.044)
INC	−0.060	0.133***	−0.072***	−0.002	−0.009	−0.074***	−0.016	−0.042	−0.040***	0.088**	−0.047***	0.070
	(0.045)	(0.043)	(0.027)	(0.034)	(0.018)	(0.024)	(0.039)	(0.045)	(0.010)	(0.035)	(0.018)	(0.075)
Called Three Times	−0.091	0.038**	0.019	0.034	0.008	−0.005	0.104	−0.018	−0.052	0.002	−0.021	−0.085***
	(0.102)	(0.019)	(0.068)	(0.070)	(0.017)	(0.025)	(0.060)	(0.102)	(0.042)	(0.044)	(0.024)	(0.022)
Caste Reservation	0.055	−0.010	−0.073	0.027	−0.007	0.011	−0.015	0.010	−0.024***	0.074***	0.013	−0.063***
	(0.062)	(0.031)	(0.046)	(0.030)	(0.029)	(0.014)	(0.028)	(0.062)	(0.006)	(0.024)	(0.012)	(0.012)
Constant	−0.012	0.099	−0.349***	1.262***	1.003***	1.012***	0.745***	0.998***	0.668***	0.123***	0.531***	0.176***
	(0.136)	(0.195)	(0.111)	(0.214)	(0.051)	(0.095)	(0.060)	(0.136)	(0.080)	(0.032)	(0.050)	(0.050)
Observations	388	388	388	388	388	388	388	388	388	388	388	388
Note:												**p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, state fixed effects, and cluster robust standard errors.

Table SI.6.6: Added Crime Control

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	−0.027	−0.016	0.005	0.039	−0.021	0.031	−0.023	0.024	0.017	0.054	0.062***	0.011
	(0.047)	(0.042)	(0.045)	(0.054)	(0.038)	(0.026)	(0.034)	(0.047)	(0.026)	(0.034)	(0.023)	(0.020)
Diversity	0.421	−0.371	0.167	−0.217	0.018	−0.022	−0.060	−0.010	0.026	0.003	−0.008	−0.132
	(0.232)	(0.243)	(0.171)	(0.257)	(0.095)	(0.076)	(0.170)	(0.232)	(0.133)	(0.156)	(0.075)	(0.190)
Contact	−0.010	0.108	0.416**	−0.515**	−0.105	−0.107	0.053	0.020	0.130	0.249**	0.227***	0.102
	(0.144)	(0.189)	(0.186)	(0.204)	(0.109)	(0.073)	(0.136)	(0.144)	(0.075)	(0.110)	(0.081)	(0.150)
Female	0.011	0.006	0.017	−0.033	−0.007	0.014	−0.022	0.002	0.008	0.002	0.020	0.013
	(0.048)	(0.049)	(0.037)	(0.040)	(0.024)	(0.026)	(0.039)	(0.048)	(0.021)	(0.026)	(0.029)	(0.019)
Age	0.004	0.003	0.003	−0.010***	−0.001	−0.002	−0.002	−0.002	0.0001	0.005**	0.003**	−0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
Social Media Active	0.164***	−0.014	0.030	−0.179***	−0.035	0.002	−0.085	−0.039	0.066**	0.057	0.095***	−0.006
	(0.064)	(0.033)	(0.042)	(0.049)	(0.024)	(0.025)	(0.047)	(0.064)	(0.029)	(0.047)	(0.025)	(0.046)
Bachelor's Degree	−0.034	0.061	0.051	−0.078	−0.040**	−0.049	−0.041	−0.049	0.018	0.088***	−0.003	0.033
	(0.043)	(0.057)	(0.036)	(0.052)	(0.019)	(0.027)	(0.038)	(0.043)	(0.014)	(0.033)	(0.020)	(0.025)
Multi-Term	−0.018	−0.014	0.021	0.011	−0.032	−0.023	−0.038	0.012	−0.028	−0.072***	−0.0004	0.060**
	(0.036)	(0.043)	(0.050)	(0.045)	(0.027)	(0.026)	(0.040)	(0.036)	(0.027)	(0.025)	(0.026)	(0.028)
BJP	−0.046	0.053	−0.052	0.045	−0.022	−0.0003	−0.028	0.016	−0.029	0.059	−0.069	0.055
	(0.056)	(0.065)	(0.038)	(0.047)	(0.048)	(0.032)	(0.055)	(0.056)	(0.032)	(0.048)	(0.037)	(0.042)
INC	−0.090	0.181**	−0.089	−0.001	−0.008	−0.077**	−0.013	−0.033	−0.049	0.085	−0.065	0.086
	(0.052)	(0.086)	(0.064)	(0.046)	(0.053)	(0.032)	(0.040)	(0.052)	(0.032)	(0.044)	(0.047)	(0.051)
Called Three Times	−0.109	0.052	0.023	0.034	0.013	−0.005	0.114***	−0.018	−0.046**	0.002	−0.025	−0.090**
	(0.071)	(0.045)	(0.046)	(0.036)	(0.031)	(0.027)	(0.036)	(0.071)	(0.022)	(0.035)	(0.030)	(0.041)
Caste Reservation	0.039	−0.004	−0.071	0.036	0.008	0.001	0.005	0.021	−0.044	0.074**	0.004	−0.044
	(0.063)	(0.044)	(0.061)	(0.049)	(0.044)	(0.023)	(0.071)	(0.063)	(0.044)	(0.034)	(0.035)	(0.022)
SC ST Crime	0.508***	−0.952***	−0.569***	1.013***	0.687***	0.489***	0.376***	0.309**	−0.373***	−0.778***	−0.009	−0.356***
	(0.158)	(0.087)	(0.114)	(0.150)	(0.109)	(0.074)	(0.095)	(0.158)	(0.063)	(0.124)	(0.111)	(0.090)
Constant	−2.806***	5.236***	2.743***	−4.173***	−2.857***	−1.551***	−1.353**	−0.649	2.651***	4.307***	0.573	2.082***
	(0.945)	(0.549)	(0.738)	(1.022)	(0.627)	(0.382)	(0.583)	(0.945)	(0.451)	(0.658)	(0.591)	(0.561)
Observations	404	404	404	404	404	404	404	404	404	404	404	404

Note: **p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, state fixed effects, and cluster robust standard errors.

Table SI.6.7: Subset to Only Forward Caste

	Dependent variable:											
	Pleasant	Unpleasant	Mixed	Weak	Spend Wisely	Opinions	Valid Concerns	One Group	Caste Trust	Neighbor	Talk	Donation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.001	0.022	−0.112	0.088	−0.044	0.021	−0.006	0.015	−0.024	−0.027	0.034	0.013
	(0.057)	(0.064)	(0.069)	(0.092)	(0.095)	(0.031)	(0.096)	(0.057)	(0.057)	(0.056)	(0.033)	(0.049)
Contact	0.127	0.208	0.201	−0.536***	−0.176	−0.007	0.029	0.108	0.171	0.278	0.203**	0.024
	(0.209)	(0.152)	(0.266)	(0.145)	(0.140)	(0.062)	(0.176)	(0.209)	(0.105)	(0.169)	(0.104)	(0.262)
Pct. Not Forward	0.639**	−0.499	0.071	−0.210	−0.169	−0.093	−0.282**	0.084	0.132	0.084	0.051	−0.008
	(0.263)	(0.287)	(0.254)	(0.226)	(0.210)	(0.139)	(0.140)	(0.263)	(0.109)	(0.143)	(0.125)	(0.338)
Female	0.043	−0.059	0.101	−0.085	−0.027	0.036	−0.066	−0.043	0.055	0.045	0.050	−0.055
	(0.081)	(0.139)	(0.077)	(0.068)	(0.041)	(0.039)	(0.098)	(0.081)	(0.036)	(0.035)	(0.055)	(0.043)
Age	0.006	0.007**	0.009	−0.023***	−0.001	−0.001	−0.009	−0.006	0.003	0.006**	0.006***	0.003
	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)	(0.002)	(0.006)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
Social Media Active	0.248***	−0.067	0.023	−0.204***	−0.049	−0.029	−0.119**	0.001	0.031	0.069	0.071**	0.032
	(0.077)	(0.073)	(0.069)	(0.060)	(0.066)	(0.032)	(0.049)	(0.077)	(0.035)	(0.069)	(0.034)	(0.066)
Bachelor's Degree	−0.092	0.112	0.121	−0.141	−0.016	−0.068***	0.009	−0.094	0.073**	0.090	0.016	0.049
	(0.070)	(0.102)	(0.094)	(0.098)	(0.045)	(0.026)	(0.057)	(0.070)	(0.034)	(0.048)	(0.029)	(0.047)
Multi-Term	−0.037	−0.038	0.090	−0.015	−0.030	−0.015	−0.067	0.011	0.016	−0.157***	0.011	0.083
	(0.073)	(0.041)	(0.072)	(0.074)	(0.048)	(0.039)	(0.092)	(0.073)	(0.050)	(0.052)	(0.041)	(0.046)
BJP	0.039	−0.072	−0.088	0.121	−0.027	0.001	−0.072	−0.069	0.021	0.036	−0.104	−0.0001
	(0.138)	(0.143)	(0.107)	(0.088)	(0.079)	(0.047)	(0.133)	(0.138)	(0.074)	(0.168)	(0.063)	(0.089)
INC	−0.051	0.045	−0.045	0.052	−0.063	−0.026	−0.036	−0.095	0.070	0.047	−0.070	−0.059
	(0.151)	(0.212)	(0.161)	(0.172)	(0.128)	(0.062)	(0.139)	(0.151)	(0.082)	(0.153)	(0.097)	(0.068)
Called Three Times	−0.038	0.023	0.059	−0.044	−0.003	0.036	0.014	−0.065	0.021	0.060	−0.021	−0.104***
	(0.080)	(0.067)	(0.080)	(0.055)	(0.046)	(0.045)	(0.083)	(0.080)	(0.042)	(0.072)	(0.036)	(0.037)
Constant	−0.410	0.007	−0.329	1.732***	0.942***	1.024***	1.153***	1.174***	0.413***	0.113	0.503***	0.071
	(0.229)	(0.263)	(0.266)	(0.262)	(0.128)	(0.087)	(0.364)	(0.229)	(0.103)	(0.195)	(0.115)	(0.141)
Observations	170	170	170	170	170	170	170	170	170	170	170	170

Note: **p<0.05; ***p<0.01

Linear regression models with dependent variables standardized between 0 and 1, corporation fixed effects, and cluster robust standard errors.

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