Facial Recognition Technology and Voter Turnout *

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Abstract

States worldwide use facial recognition technology (FRT) to assist in policing citizens, monitoring public goods, and even running elections. This article asks how FRT in polling stations affects voter turnout. Existing research on technology in elections offer ambiguous predictions for the direction and magnitude of the effect. I leverage a state-run randomized pilot of FRT in local elections in a municipality in Telangana, India to show that polling stations with FRT have lower turnout compared to those without. I discuss how three possible mechanisms might explain this effect: logistical issues, shifts in fraudulent activity, and apprehension about government surveillance particularly among marginalized citizens. Given the small sample of this pilot, the findings should be viewed as suggestive but indicative of the need for future research on the consequences that new technologies in governance can have on citizens in democracies.

Keywords: technology, turnout, India, elections, surveillance, marginalized groups

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Over the past several decades states around the world have adopted new technologies in areas such as public service delivery, safety and policing, and even elections (Bussell 2012; Cheeseman, Lynch and Willis 2018). One newer form of technology that states are using is facial recognition technology (FRT). Across the world, at least 52% of countries use FRT in police stations, airports, local transportation, and government CCTV (see Appendix 1.1). More recently, governments have introduced FRT into polling stations to reduce fraud and increase efficiency. India piloted FRT in polling stations in one municipality in Telangana state during local body elections in January 2020. As election commissions across the world pilot and roll out facial recognition software, it is important to understand its political consequences.

Existing work across a range of contexts finds that various components of election administration such as the identity of polling booth bureaucrats, rules regarding election queuing, and the use of indelible ink can impact voter turnout and behavior (Neggers 2018; Harris 2020; Ferree et al. 2018). Research on the role of technology and elections focuses on the implementation of electronic voting machines (EVMs). In Brazil, electronic voting enfranchised poorer voters prompting the government to shift funds to areas that benefited the poor such as healthcare (Fujiwara 2015). Research in India finds mixed evidence on the effect of EVMs on turnout but do note that EVMs can also make invalid voting difficult therefore encouraging voters to cast a "protest vote" for minor parties or candidates (Debnath, Kapoor and Ravi 2017; Desai and Lee 2019).

The results from these studies suggest that FRT may influence voter behavior but the magnitude and direction of the effect is theoretically unclear. Increasing citizens' confidence in the integrity of the electoral process by reducing opportunities for fraud can often increase their likelihood of turning out to vote (Birch 2010). If citizens perceive the use of FRT at polling stations as a way to reduce fraud (which was the election commission's goal) then the presence of FRT at a polling station may increase voter turnout. Alternatively, FRT can reduce voter turnout by generating logistical complications, skewing potential fraudulent voters away from FRT stations, or heightening concerns over government surveillance and greater legibility of citizens (Scott 1998), as research in post-Rose Revolution Georgia shows is possible (Driscoll and Hidalgo 2014).

I focus on the Telangana State Election Commission's (TSEC) random assignment of FRT to polling stations during the January 2020 local body elections in Kompally municipality to study the effect of FRT on voter turnout. By taking advantage of a small-scale but real-world experiment, I provide some of the first evidence, to my knowledge, on a topic of increasing importance for democracies in the age of technology. I find that polling stations with FRT had 6.7 percentage points lower turnout compared to those without. I outline three possible mechanisms that could play a role in driving this effect and provide suggestive evidence where possible. One piece of suggestive evidence indicates that the negative effect on turnout may have been stronger in polling stations with a greater share of Muslims. Indian Muslims are a marginalized group with heightened concerns about government surveillance and instant facial recognition especially in light of events in 2020 regarding India's Citizenship Amendment Act (CAA) and the National Registry of Citizens (NRC).

The paper contributes theoretically and empirically to existing work on technology and politics and the drivers of voter turnout. Yet, because the nature of this pilot was modest, focusing on a total of 36 polling stations in one municipality, I do not seek to overstate the conclusiveness or external validity of the finding. Nevertheless, I build confidence in the results by considering the generalizability of the study's setting, probing the robustness of the findings, and addressing threats to inference in several ways. Still, the results should be interpreted as suggestive and indicative of the need for an agenda of future work on how technological advancements like FRT can impact citizen's willingness to engage in democratic processes like voting.

Context: Municipal Elections in India. India—the world's largest democracy and the setting of this study—is consistently at the forefront of election technology making it an ideal case (see Appendix 1.2). In January 2020, in the municipality of Kompally (located about 25 kilometers outside of India's fourth largest city of Hyderabad), the Telangana State Election Commission (TSEC) randomly assigned FRT to 10 of the 36 polling stations to verify the identity of voters before they voted. Further details about the 2020 elections, Kompally municipality, and how this location compares to other areas located outside of major cities are included in Appendix 1.3 and 1.4. This was the first time FRT was used in the electoral setting in India. Yet, as of October 2021, the Indian Freedom Foundation's Panoptic Project found that states had installed FRT for 66 distinct projects across 16 Indian states (see Appendix 1.2). TSEC made the decision to pilot FRT organically suggesting a willingness to use it more widely. In fact, TSEC planned to implement FRT in 150 polling stations in Hyderabad municipal elections in December 2020 but technical difficulties led to canceling the effort.

A TSEC circular outlined the procedure for stations with FRT. The first polling officer who is in charge of voter identification took a photo of the voter, uploaded it to the server, and then received notice in less than 30 seconds whether it matched the photo of the voter on file. In the status quo and in the polling stations without FRT the polling officer would verify an individual's identity by manually checking their voter roll photo. TSEC indicated that the use of FRT was to reduce impersonation which polling stations had previously experienced, especially with regard to impersonating absent, shifted, or dead voters. The circular emphasized that all data would be encrypted and then deleted immediately after the authentication process. There was no indication that this was adopted for nefarious purposes.

Overall the FRT application yielded an 80% match rate. Voters whose photos did not match were *not* turned away from voting since the effort was a pilot.[1] TSEC informed voters

[1]At non-FRT stations, officers were able to turn away voters who did not match their photo on file through the manual verification process. While I do not have data on the number of voters turned away from non-FRT stations, this fact pushes in the opposite direction of finding a reduction in turnout at treatment stations compared to control stations.

ahead of time through several mediums that their assigned polling station would use FRT. Crucially, citizens must vote in their assigned polling station unless they register a change of address. So if a voter did not want to experience FRT their only option was to not vote.

Empirical Approach: Pilot of FRT in Polling Stations. To examine the impact of facial recognition technology on voter turnout, I take advantage of the random assignment of FRT to polling stations in Kompally municipality. The TSEC circular and correspondence with the TSEC secretary who oversaw the pilot indicate that the technology was randomly assigned and not determined by characteristics of the polling station. I further verify this with balance statistics in Table 1. When comparing treated and untreated polling stations the only statistically significant differences in the pre-treatment covariates are for the percent Muslim (exact p-value = 0.09 and 0.07) and the number of eligible voters (exact p-value = 0.09). It's unlikely that FRT was intentionally assigned to stations with more Muslim voters since religion is not included on the voter rolls (I estimate this using a name to religion methodology). Nevertheless, I control for these and other covariates in some of the models and find similar estimates.

For the main result, I estimate the following OLS model: $y_{il} = \beta FRT_i + \alpha_i + \delta_l + \epsilon_{il}$. In the model, y_{il} is the turnout in polling station i for election l. Turnout includes everyone who casted a vote. Individuals who were not authenticated by the technology were not turned away from voting so they are also included in the turnout measure. FRT_i is the treatment variable coded as a 1 if poll workers used FRT at polling station i and 0 otherwise. α_i are polling station i control variables and δ_l are election l control variables. ϵ_{il} is a station-election error term. The analysis is limited to the 36 polling stations in Kompally that TSEC considered for FRT. Because of this small sample size, I use exact p-values through randomization inference (described in detail in Appendix 2.3).

FRT Reduces Voter Turnout. Table 2 reports a negative and statistically significant effect of FRT on turnout. The main result in Model 1 without controls indicates that polling stations with FRT had 6.7 percentage points lower turnout than polling stations without

Table 1: Balance Table for Key Variables

Variable	No FRT Means	FRT Means	Difference in Means	Exact P-Value
Total Eligible Voters	687.88	700.70	-12.82	0.09
Male Eligible Voters	349.88	356.90	-7.02	0.23
Female Eligible Voters	337.85	343.40	-5.55	0.35
Number of Parties	3.15	3.00	0.15	0.31
Percent Muslim (1)	9.55	13.66	-4.11	0.09
Percent Muslim (2)	7.33	16.14	-8.81	0.07
Gender Reservation	0.42	0.70	-0.28	0.26
SC / ST Reservation	0.12	0.10	0.02	1.00
BC Reservation	0.46	0.20	0.26	0.26
General Election Turnout	0.54	0.56	-0.02	0.33

Notes: Exact p-values are calculated using randomization inference. I use two approaches to determine the percent of Muslims, these are described in Appendix 3.6.

FRT. Models 2 and 3 control for election pre-treatment covariates and polling station pre-treatment covariates separately, finding similar negative effects (although Model 3 is not statistically significant). Model 4 controls for both election and polling station covariates and finds a statistically significant negative effect. Model 1 and 4 are preferred as they show the effect without any control variables and with all relevant control variables – both show a significant negative effect of FRT on turnout with similar magnitudes. The magnitude of this negative effect is large and in Appendix 3.1 I discuss how an effect of this size could influence electoral outcomes. To probe the robustness of this result, I use a covariate adjustment method in Appendix 3.5, control for general election turnout in Appendix 3.3, control for post-treatment variables in Appendix 3.4, and use a difference-in-difference design in Appendix 3.6.[2] Taken together, the results are mostly statistically significant and are always in the expected negative direction, suggesting that FRT reduced turnout.

Mechanisms for Reducing Voter Turnout. I theoretically outline how three mechanisms (logistics, voter / party fraud, and surveillance concerns) may contribute to lower turnout and provide empirical evidence where possible. First, it is possible that logistics could lead to a reduction in turnout. If the technology takes a long time to operate this could generate longer lines which could discourage voters from waiting to cast their vote. Moreover, even if there was not a longer line, the perception that there might be due to FRT could be

[2] I note that there are downsides to several of these approaches and discuss them in the respective sections in the Appendix.

Table 2: Effect of Facial Recognition Technology on Voter Turnout

	Dependent variable:			
	(1)	(2)	(3)	(4)
Facial Recognition Technology	-6.66	-9.67	-5.48	-8.05
	(4.16)	(4.26)	(4.40)	(4.23)
	[0.09]*	[0.01]***	[0.27]	[0.05]**
Mean of DV	65.98	65.98	65.98	65.98
Election Controls	N	Y	N	Y
Polling Station Controls	N	N	Y	Y
Observations	36	36	36	36

Notes: Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01. Exact p-values are reported in brackets. Election controls are the number of parties and a reservation indicator. Polling station controls are the total number of eligible voters assigned to a station, the percent of eligible voters who are female, and the estimated percent of Muslims in the polling station. In Appendix 2.1 I show summary statistics for all variables. In Appendix 3.2 I explore turnout by gender.

enough to lead some voters to stay at home. Video recordings of the FRT process from the *Times of India* indicate that it took less than 30 seconds for the application to verify an individual voter. It is possible that this is a longer process than manually verifying a voter. Overall, logistics remains a mechanism that plausibly contributed to the lower turnout in FRT stations.

Second, both voter fraud or party-planned fraud could drive lower observed turnout. Voters who intend to cast a fraudulent ballot by impersonating another individual on the voter roll could shift to voting in a non-FRT station to avoid the possibility of being discovered. In this case, the negative effect of FRT on turnout could be a consequence of less fraud at FRT stations (so lower observed turnout in FRT stations), more fraud at non-FRT stations (so higher observed turnout in non-FRT stations), or a combination of both. In Appendix 3.9, I examine if FRT has spillover effects on turnout in non-FRT stations. I find that non-FRT stations in the same physical school as FRT stations did not have any statistically significant difference in turnout. And, while I cannot rule out the possibility of fraud spillover playing a role in these effects, in the 2020 elections, TSEC discovered 4 impersonation cases none of which were observed in the district where Kompally is located. However, it is still possible for impersonators to collude with election officials in such a way that it remains undiscovered, making shifts in fraudulent voters a potential contributor to lower observed turnout.

At the political party level, it is possible that polling stations with FRT prevented fraud that parties planned to engage in. This in turn could make parties use different methods such as using muscle power to capture booths or using party workers to distribute handouts, generating key differences that could affect voter decisions (Vaishnav 2017; Chauchard 2018). In the context of Telangana, this should be less of an issue because the greater Hyderabad area is not known for high levels of booth capture. Live update reporting during the 2020 elections from the *The Times of India* and *Indian Express* corroborate this by identifying no instances of party worker interference in Kompally or the broader Telangana municipalities. Moreover, the Kompally municipality itself is 6 square miles and the polling stations were concentrated at a few key schools suggesting that it would be difficult for party-led efforts to exclusively impact FRT stations.

A final explanation is that FRT lowers turnout by actively demonstrating the government's ability to identify an individual with just one photo in the matter of a minute. The government's ability to do this could be especially worrisome for marginalized groups like Muslims who, a few weeks prior to the election, witnessed and read about the government using the same technology to identify protesters against the CAA / NRC. In some reporting Muslims indicated that while protesting they even wore handkerchiefs to cover their faces from being identified through FRT.[3] Still, as noted earlier, technology is widely used in Indian governance and elections so it may be difficult for one additional photograph in the voting process to deter so many voters. Alternatively, the aversion to voting due to FRT may stem from the government's demonstration of its identification capabilities not necessarily just that they are able to collect one additional photo.

To examine if the lower turnout is driven by government surveillance concerns, I focus on if the negative effect on turnout is concentrated among marginalized groups, particularly Muslims. I test whether polling stations with more Muslim voters see a greater negative

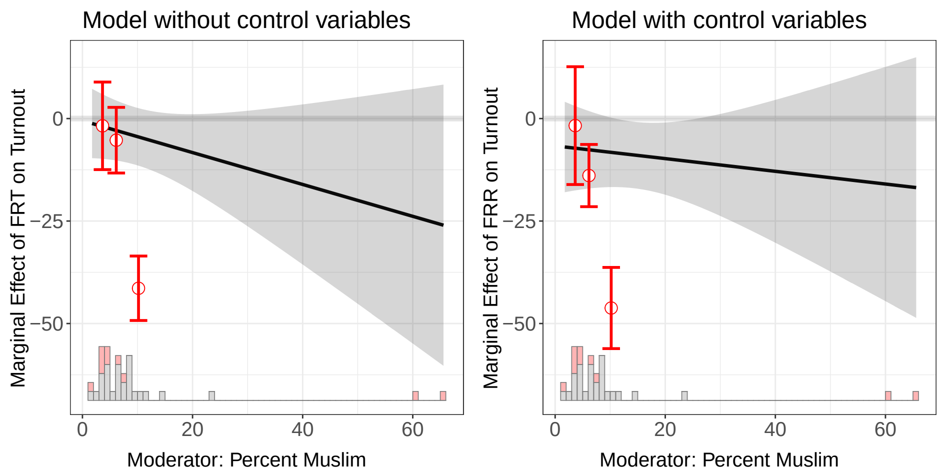
[3] See: India's use of facial recognition tech during protests causes stir

impact on turnout. I estimate the percent of Muslims in each polling station using individual names on the voter rolls.[4] The full procedures to obtain these estimates are discussed in Appendix 3.7. Figure 1 shows the marginal effects plot using the binning estimator to model the interaction effect of the percent of Muslims and FRT use on voter turnout (Hainmueller, Mummolo and Xu 2019). The plot shows that it is possible that polling stations with more Muslims saw a greater decrease in turnout. However, as discussed with the full results and different specifications in Appendix 3.7, the results do not consistently hold. Moreover, places with more Muslims are often correlated with higher poverty, worse access to schools, and less public hospitals (Adukia et al. 2019). This could mean that that stronger negative effect of FRT on turnout is due to underlying factors such as lower education rather than apprehension about government surveillance among Muslims. To complement these results, I examine if FRT is related to a decrease in the vote share for parties that Muslims are more likely to support. Appendix 3.8 shows that there is a negative association between FRT and vote share for two parties that Muslims vote for and a positive association between FRT and vote share for the party that Muslims rarely support, however, these results are not statistically significant. Finally, in Appendix 3.10 I use qualitative evidence from the reaction of a Muslim political party to show that Muslims in particular were concerned about FRT.

Underlying the aforementioned voter-focused mechanisms is the assumption that voters were aware of FRT's use. The process of gaining information about FRT use can occur through several possible channels: ahead of election day through the election commission and party communications, on election day at the polling stations by an individual voter themself, or on election through someone else who went to the same polling stations earlier. In Appendix 2.2, I present evidence from TSEC and Google trends data that it is possible

[4]Existing work shows that names can be used to reliably predict ethnicity in the US and Kenya and religion in India (Harris 2015; Susewind 2015; Neggers 2018; Chaturvedi and Chaturvedi 2020)

Figure 1: Marginal Effects Plots



Notes: The plot shows the marginal effect of FRT on turnout at varying levels of percent of Muslims in a polling stations using the binning estimator.

that at least some voters were aware that FRT was being used in particular polling stations in the local elections.

Discussion and Conclusion. In the past several decades there has been an expansion of technologies related to identification including social security numbers, biometric IDs, CCTV, and facial recognition technology. As these forms of technology enter into democratic governance, they can influence the ways that different groups engage in democratic practice. For example, in settings with low trust in government, citizens who are concerned about surveillance may react to the infusion of identification-related technology into electoral processes by disengaging in the voting process. It is also possible that if fraudulent electoral activity is influenced by new surveillance technologies in elections, political actors can displace impersonation votes to lesser-developed areas that are not able to adopt these new technologies as rapidly. As governments continue to use FRT and related technology, it is possible that over time, in equilibrium, citizens will become accustomed to it and any negative effects will dissipate. Nevertheless, this study demonstrates that in the time it takes for FRT to be normalized, it could have a tremendous impact on how citizens participate in politics in democracies.

This paper offers a first empirical examination of the political consequences of facial recognition technology. I find that in an Indian pilot of FRT, voter turnout was lower in polling stations with FRT. I then discuss how logistics, fraudulent activity, and concerns about government surveillance could each contribute to this effect. As these results are suggestive, this study indicates the need for more work to confirm the negative effect on turnout, explore additional political consequences, and further examine the proposed mechanisms. If governments continue, as expected, to scale up these technologies in elections, it will be critical to determine how to use the technology in a way that does not reduce citizen engagement with one of the cornerstones of democracy: voting.

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Online Appendix

Contents

A 1 Context

A 1.1 Worldwide FRT Use

Facial recognition technology is used in at least 52% of countries worldwide. The variation of FRT use across the world is shown in Figure A 1. The data which can be found here is from SurfShark, a technology company. They collected the data based on news articles about FRT use in each country. Countries were assigned a status of “in use” if there exists evidence of the government using facial recognition technology in some surveillance or public security capacity. The data was retrieved on June 29, 2020.

While FRT is used in other areas of governance, it has only recently made its way into the realm of voting. The first known use of FRT in elections was in Afghanistan’s presidential elections in September 2019. Biometric machines used fingerprint scans and face photos to identify voters. The use of FRT in the local elections in Telangana represents the second known use.

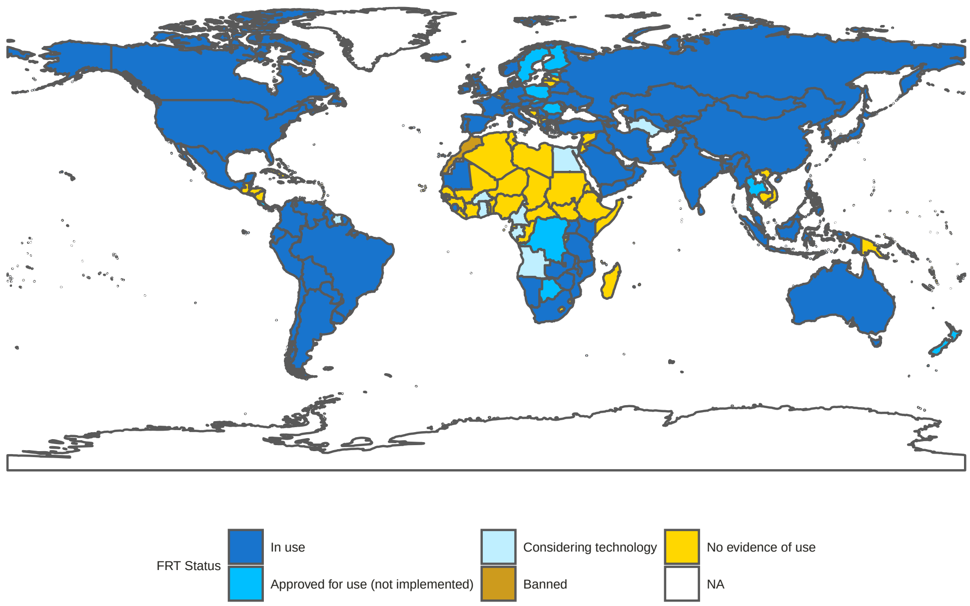


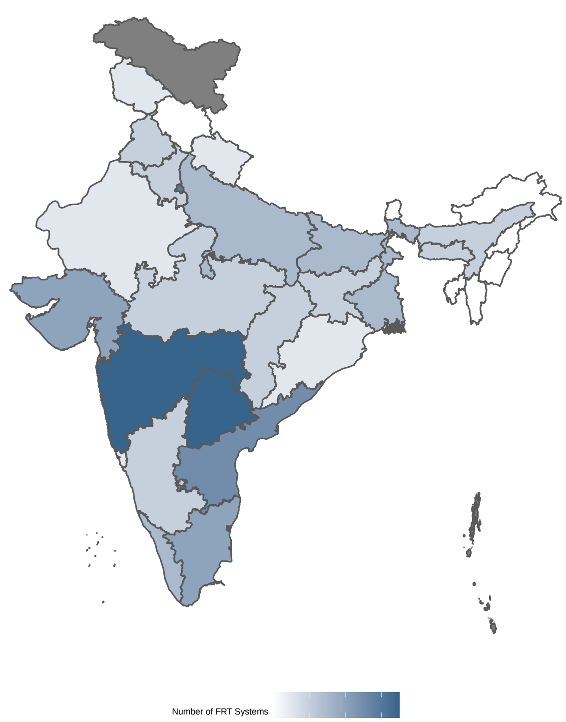
Figure A 1: Use of facial recognition technology worldwide. The data for this map (which can be found here) comes from SurfShark, a technology company. The in use option was assigned to countries where there is a record in news articles or other sources indicating the use of facial recognition technology in the country

A 1.2 Technology and FRT in India

India is consistently at the forefront of using technology in elections making it an ideal case to examine. In 1998, EVMs were piloted in a bye-election in Kerala and used more widely the following year in the general elections (Debnath, Kapoor and Ravi 2017). Today, India uses biometric data in voter registration, electronic voting machines for virtually all elections, an electronic tabulation system for determining results, and an online database with voter lists and election results. Outside of elections, the Indian government uses Aadhaar, the world's largest biometric ID system, to help distribute welfare schemes; however, this program has come under criticism for privacy and surveillance issues (Khera 2019).

Data collected in October 2021 suggests that facial recognition technology is installed to be used in 16 states across Indian 66 total projects. Figure A 2 shows the distribution in the number of FRT systems across the country. The data is from the Panoptic tracker run by the NGO India Internet Freedom. Their data indicates that FRT is primarily used by state police forces. Telangana is the only state at their time of data collection that uses FRT in elections.

Figure A 2: Use of facial recognition technology in India



A 1.3 Kompally Municipality and the 2020 Local Body Elections

In January 2020, the Telangana State Election Commission (TSEC) oversaw elections for over 2,900 wards located in 120 municipalities and 9 corporations. The election made use of over 7,900 poll stations with over 45,000 workers overseeing the process. These elections have relatively high turnout and are pretty fiercely fought. Across all of Telangana the average voter turnout in this municipal election was 70% which is greater than the most recent national elections (62% in Telangana) and about the same for state-level elections.

In the municipality of Kompally in the Medchal-Malkajgiri district, the election commission randomly assigned FRT to 10 of the 36 polling stations to verify the identity of voters before they voted. This was confirmed this with the Telangana State Election Commission when accessing the data. Moreover, this randomization process is in line with Telangana's use of a computer software to randomize various components of election administration such as polling station bureaucrats and EVMs (See: Telangana's randomization manual, Telangana's randomization platform, and reporting on previous randomization by TSEC). The randomization to actual FRT use had perfect compliance. This is verified through confirmation from the Telangana State Election Commission and by comparing the announced FRT polling station numbers with the data on polling station turnout and FRT status. All together this suggests that the randomization process from TSEC is credible. The facial recognition application was developed by the Telangana State Technology Services and loaded onto 10 smartphones. The TSEC made the decision to pilot FRT organically indicating that there is a possibility for this to be scaled up in the future.

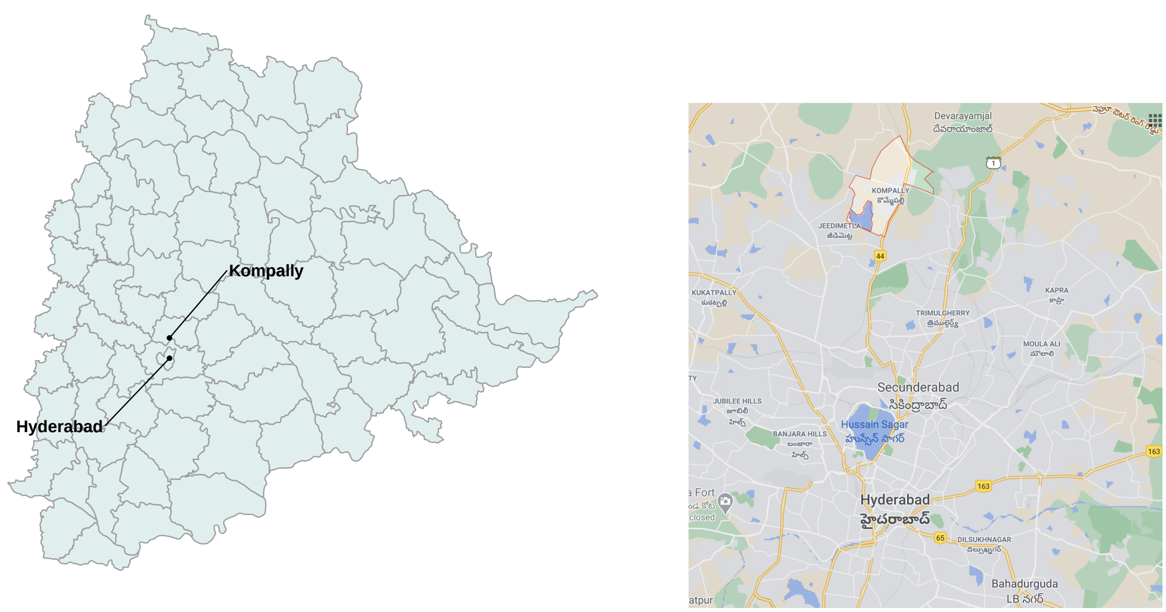
Kompally is located about 20 kilometers north of Hyderabad. The municipality is 17 square kilometers (6 square miles) in area and has a total population of 22,377 according to the 2011 Census of India. Figure A 3 shows the size and location from Google maps. Kompally is divided into 18 wards and 2 polling stations were used in each ward. Ward member elections were the only item on the ballot.

Ward members (also known as councilors and corporators) are elected for 5 years and have many responsibilities including water supply, public transportation, roads, street lights, drainage, local education, and health services such as hospitals. The municipality governance is funded through local taxes and grants-in-aid from the state and national government (Gaikwad and Nellis 2021). The elected councilors also elect a mayor who plays a mostly ceremonial role.

Existing work that studies corporators notes that they interface with citizens regularly to help solve their problems – one ethnography of a corporator in Gujarat notes that the corporator deals with questions and requests from 30-40 citizens in two hours (Berenschot 2010). In their study of municipal corporators, Gaikwad and Nellis (2021) also highlight the key role of corporators in helping with citizens problems. They write, "when problems arise, citizens turn to their local councilor for help. Councilors can notarize documents, put in calls and formal requests to zonal and ward-level officers, spend their discretionary funds to fix particular issues, or seek the intervention of higher-up politicians to solve thornier problems" (Gaikwad and Nellis 2021, 794). Given the central role of municipal governance, voters are generally attentive to local elections often turning out at higher rates in local elections compared to national elections (as the data in Telangana indicates, 70% turnout in municipal elections compared to 62% in national elections).

In this part of Telangana, electoral competition generally involves the Bhartiya Janata Party (BJP), the Indian National Congress (INC) (and sometimes their ally the Telugu Desam Party (TDP)), and the Telangana Rashtra Samithi (TRS). Kompally's member of the legislative assembly is currently K.P. Vivekananda of the TRS and their Member of Parliament is Revanth Reddy of the INC.

Figure A 3: Map of Kompally Municipality



A 1.4 Comparing Kompally to other areas

This study focuses on the municipality of Kompally. While it is difficult to determine whether the negative effect I observe on turnout would also exist in other municipalities, I provide evidence in this section that the district that Kompally is part of is relatively similar on many characteristics to other districts located just outside major cities in India.

In 2011, Kompally municipality was located in the Ranga Reddy district of the state of

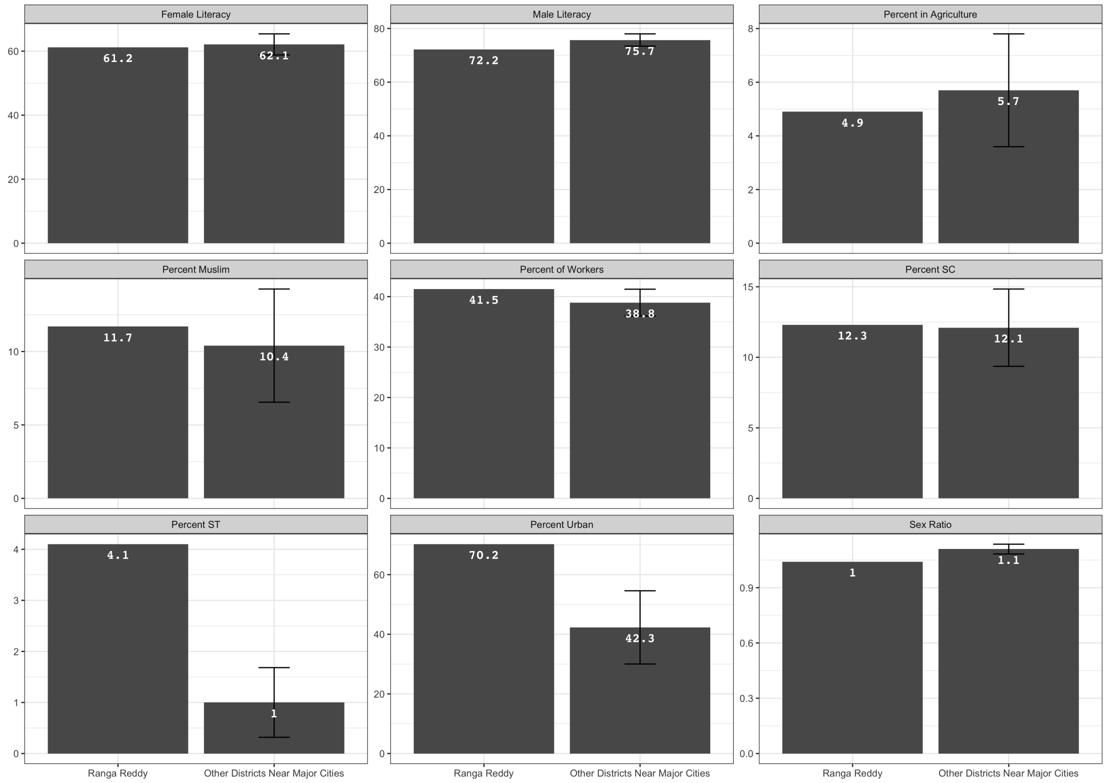
Andhra Pradesh.[1] This district is located right outside of Hyderabad, India's fourth largest city. To see how similar the district of Ranga Reddy is to other districts outside of major cities in India, I identify all districts that border a district that has one of the 5 major cities in India. Table A 1 shows a list of these districts, which city they border, and what state they are located in. Figure A 4 shows how Ranga Reddy compares to other districts outside of major cities on key demographic and other variables from the 2011 Census of India. In general, Ranga Reddy is similar to these other districts on literacy, percent Muslim, percent Scheduled Caste, sex ratio, percent working, and percent working in agriculture. Ranga Reddy is more urban and has a higher share of STs compared to other major districts. If it is the case the FRT may be more likely to deter turning out for marginalized groups, then Ranga Reddy having a higher share of Schedule Tribes may mean the the effect I observe is greater than what we may observe for other districts. On the other hand, if it is the case that more urban voters are less likely to be apprehensive about FRT because of more exposure to technology in general, then the effect I observe may be a lower bound. While I cannot generalize the findings to these other districts, it does appear that Ranga Reddy, where Kompally is located, is similar to other districts outside of large Indian cities.

[1]Today, Kompally is part of the Medchal-Malkajgiri district in the state of Telangana. In 2014, Telangana was carved out of Andhra Pradesh as a separate state.

Table A 1: List of districts bordering the 5 largest cities in India

District	Bordering Major City	State (in 2011)
Ranga Reddy	Hyderabad	Andhra Pradesh
Jhaggar	Delhi	Haryana
Gurgaon	Delhi	Haryana
Sonipat	Delhi	Haryana
Faridabad	Delhi	Haryana
Bhagpat	Delhi	Uttar Pradesh
Ghaziabad	Delhi	Uttar Pradesh
Gautam Buddha Nagar	Delhi	Uttar Pradesh
Mumbai Suburban	Mumbai	Maharashtra
Ramannagara	Bangalore	Karnataka
Bangalore Rural	Bangalore	Karnataka
Krishnagiri	Bangalore	Karnataka
Bhavnagar	Ahmedabad	Gujarat
Surendranagar	Ahmedabad	Gujarat
Mahesana	Ahmedabad	Gujarat
Gandhinagar	Ahmedabad	Gujarat
Kheda	Ahmedabad	Gujarat
Anand	Ahmedabad	Gujarat

Figure A 4: Comparing Ranga Reddy district to districts outside major cities



A 2 Data and Identification

A 2.1 Data and Summary Statistics

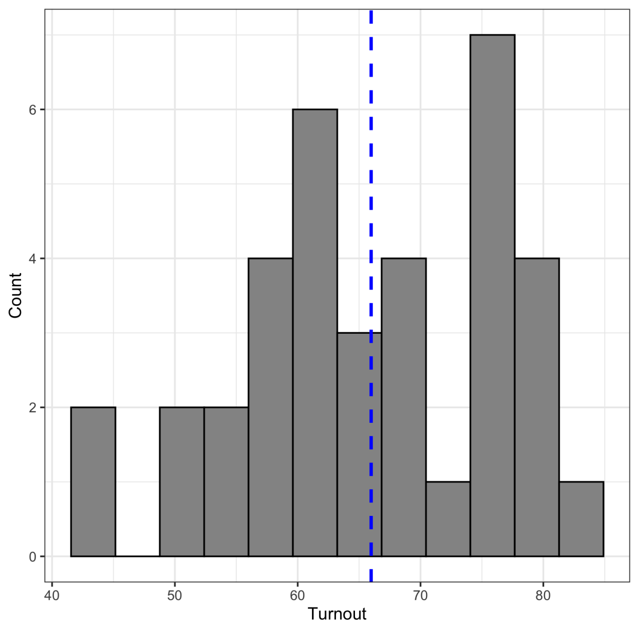
To study the effect of FRT on voter turnout I obtained and digitized polling station turnout data and ward level election results. Obtaining polling station level data for a local election as opposed to a state or national election in India is incredibly difficult because this granular data sits with individual commissioners for each municipality. I was able to obtain turnout data at the polling station level from the assistant secretary at the election commission who helped coordinate with the municipality commissioner. This is one of few papers in the Indian context that uses polling station level results for a *local* election.

Table A 2 provides summary statistics for key variables used in analysis. Figure A 5 shows the distribution of the dependent variable, voter turnout in the 2020 local elections in Kompally municipality in Telangana state.

Table A 2: Effect of the Sacred Time on Religious Riots

Variable	Mean	SD	Min	Max	N
Turnout	65.98	10.68	43.12	82.86	36
Facial Recognition	0.28	0.45	0.00	1.00	36
Male Turnout	65.88	10.64	45.82	81.82	36
Female Turnout	66.17	11.01	40.55	83.91	36
Total Eligible	691.44	20.42	651.00	722.00	36
Male Eligible	351.83	15.28	323.00	385.00	36
Female Eligible	339.39	15.72	314.00	376.00	36
Share of Female	49.08	1.67	45.35	52.29	36
Number of Parties	3.11	0.32	3.00	4.00	36
Percent Muslim (M1)	10.69	7.54	5.47	41.08	36
Percent Muslim (M2)	9.78	13.66	1.75	65.58	36
Gender Reservation	0.50	0.51	0.00	1.00	36
SC / ST Reservation	0.11	0.32	0.00	1.00	36
BC Reservation	0.39	0.49	0.00	1.00	36
General Election Turnout	0.54	0.05	0.44	0.65	26

Figure A 5: Distribution of Turnout in 2020 Kompally Local Elections



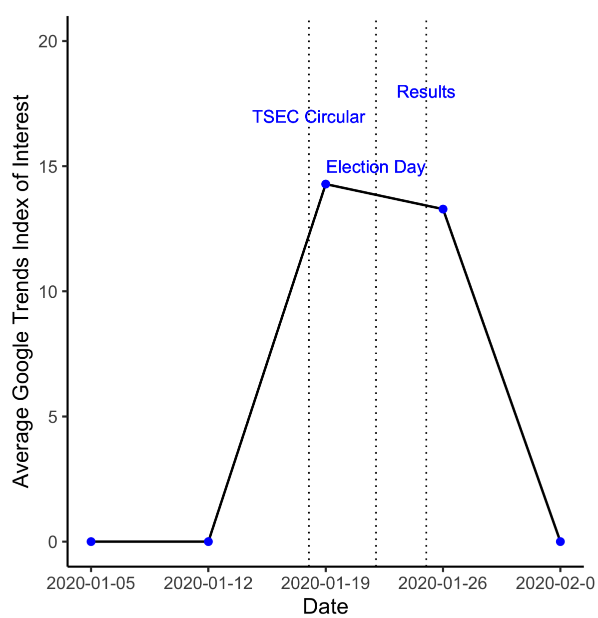
The dashed line indicates the mean turnout

A 2.2 Citizen's Knowledge of FRT

To be sure that I'm estimating an effect of FRT on turnout I present evidence from TSEC and Google trends that voters assigned to FRT stations were aware of the use of FRT prior to the election. Five days before the election TSEC released a circular detailing the facial recognition technology and which polling stations would be using it. TSEC also called a press conference with reporters, party leaders, candidates, and the public where they explained the technology, their rationale for its use, and which polling stations would have FRT. All details were also reported in national and local newspapers and on local news stations in Hindi, Telugu, and Urdu suggesting that the public was very aware of the FRT status of their station.

Beyond the fact that TSEC informed voters of this through press conferences and print and television media, I provide some evidence that voters may have been indeed aware of the use of FRT leading up the election. I use Google search data to show that searches for the term "facial recognition" (in quotes) increased after the announcement of usage at the polls. The plot in Figure A 6 shows Google search interest in "facial recognition" for the state of Telangana in the two weeks before and the two weeks after the election. One option would be to compare the searches for "facial recognition" in Telangana to another similar state, ideally Andhra Pradesh which Telangana was part of until 2014. The search for "facial recognition" in Andhra Pradesh remained at zero for the same time period. This offers some additional evidence that voters were aware of FRT in polling stations.

Figure A 6: Google Search Interest for "Facial Recognition" in Telangana



A 2.3 Randomization Inference

Given the small sample size ($n = 36$), for all analyses I use randomization inference to determine how likely it is that the differences in voter turnout would have arisen by chance (Fisher 1935). Randomization inference calculates the p-value under a sharp null hypothesis of no effect of FRT on turnout for all observations. Using 100,000 randomly generated artificial treatment and control assignments, I calculate the p-value which represents the share of the generated treatment effects that have a larger magnitude than the true treatment effect. These exact p-values do not make assumptions about the distribution and are increasingly recommended and used for small sample experiments (Gerber and Green 2012; Kalla and Broockman 2016).

A 3 Additional Analysis and Robustness

A 3.1 Substantive Effect of FRT

I find that polling stations with FRT had 6.7 percentage points lower turnout than stations without the technology. To understand the substantive effect of the estimate of FRT on voter turnout, I conduct a back of the envelope calculation. I use the main model estimate to see whether the 6.7% lower turnout could change the winner of the ward member elections. To do this I can examine the margin of victory in the 12 ward elections that did not have FRT in either of their 2 polling stations. If we assume that one-third of the voters who stay at home due to FRT would have voted for the winning candidate, then ward races with a 2.23% ($6.7 \times \frac{1}{3}$) margin of victory or lower would have had a different result. In the case of Kompally, that's 2 out of 12 races or 16.67% of races. This provides preliminary evidence that the decrease in turnout from FRT could be consequential enough to alter electoral outcomes.

A 3.2 FRT and Gender

This section presents the effect of facial recognition technology on male and female voter turnout. Table A 3 shows the effect of FRT on male and female turnout. There is a negative effect of FRT on male (exact p-value = 0.11) and female turnout (exact p-value = 0.09). In this context, we do not find a stronger negative effect for female voters. Journalist coverage of FRT usage in the Afghanistan election raised concerns about female head and face covering being an impediment to female turnout when FRT is when. I do not find evidence of this for Kompally municipality so it remains possible that in areas where women wear burqas or niqabs they may be less willing to show up if FRT will be used to verify their identity.

Table A 3: Effect of Facial Recognition Technology on Turnout by Gender

	Dependent variable:	
	Male Turnout	Female Turnout
	(1)	(2)
Facial Recognition Technology	−6.29	−6.94
	(4.03)	(4.38)
	[0.11]	[0.09]*
Mean of DV	65.88	66.17
Observations	36	36

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01.

A 3.3 Controlling for General Election Turnout

There is no available data for the local body elections in Kompally before 2020. In 2019, Kompally municipality was constituted from two gram panchayats (Kompally and Dullapalli) given their growth. The previous local elections were in 2014 and there is no data available from TSEC for gram panchayat elections during this time. In order to control for previous turnout I use a measure of turnout at the same polling stations from the 2019 general elections. This reduces the sample size from 36 to 26 since there were only 26 polling stations that were used both in the 2019 general elections and the 2020 local elections. One issue with this approach is that the voter lists change each election cycle so the voters who were assigned to each polling station in 2020 were not necessarily the same as those who were assigned in 2019. Nevertheless the results, shown in Table A 4, are all in the negative direction. The results are not statistically significant; however, this is not surprising given the number of observations is 26.

Table A 4: Effect of Facial Recognition Technology on Turnout (Controlling for Previous Turnout)

	Dependent variable:	
	(1)	(2)
Facial Recognition Technology	−6.95	−5.60
	(5.13)	(7.68)
	[0.12]*	[0.43]
Mean of DV	64.25	64.25
Previous Turnout Control	Y	Y
Election Controls	N	Y
Polling Station Controls	N	Y
Observations	26	26

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01.

A 3.4 Controlling for Post-Treatment Variables

Generally, methodologists advise against conditioning on post-treatment variables (Montgomery, Nyhan and Torres 2018) so in the main models I do not include any post-treatment variables derived from the outcome of the elections. For robustness, I show that the results are similar even if we do control for two post-treatment measures of the competitiveness of the ward election. The first is the effective number of parties (ENOP) which is an adjusted number of political parties based on the vote share of each party received. The second is margin of victory which is calculated by subtracting the vote share of the runner-up from the winner. Table A 5 shows that the results from incorporating these post-treatment variables are consistent with the main findings.

Table A 5: Effect of Facial Recognition Technology on Turnout (Controlling for Post-Treatment Variables)

	Dependent variable:	
	(1)	(2)
Facial Recognition Technology	−7.47	−6.61
	(4.16)	(4.84)
	[0.07]*	[0.1]*
Mean of DV	65.98	65.98
Post Treatment Controls	Y	Y
Election Controls	N	Y
Polling Station Controls	N	Y
Observations	36	36

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01.

A 3.5 Covariate Adjustment Using Lin (2013)

When estimating an average treatment effect (ATE), Freedman (2008) shows that pre-treatment covariate adjustment can bias estimates of the ATE. Lin (2013) proposes an estimate that reduces this bias and improves precision. The process involves regressing the outcome variable (voter turnout in my case) on the treatment (FRT), centered pre-treatment covariates (number of parties, reservation indicator, total eligible voters, percent of female eligible voters, and estimated percent of Muslims), and interactions of all pre-treatment covariates and the treatment (FRT). The results in Table A 6 show that there is a statistically significant negative effect of FRT on turnout on the order of a 4.89 percentage point reduction.

Table A 6: Effect of Facial Recognition Technology on Turnout (Using Covariate Adjustment from Lin (2013))

	Dependent variable:
Facial Recognition Technology	-4.89^{*}
	(2.663)
	[0.08]
Mean of DV	65.98
Observations	36
Election Controls	Y
Polling Station Controls	Y

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01.

A 3.6 Difference in Differences Analysis

This section presents the difference-in-differences analysis using a polling station location level dataset. Because there is no data on the last local body election at the polling station level, I compare turnout from the 2019 general election to the 2020 local elections in treated and control polling stations.[2] The polling station location is different from using the polling station as the unit of observation. While in the 2020 local elections two polling stations could be at the same location, in the 2019 general elections only one station was assigned to a location (likely because more voters could be on a polling station's voter list). I use turnout in the polling stations from the 2019 general election as the pre-period and turnout in the 2020 local election as the post-period. Because a different number of polling stations is used in general and local elections, there are only 15 total station locations that are used in both the 2019 and 2020 election (30 observations across both time periods). Moreover, voter lists for each station changes over time, the same voters who were assigned in 2019 are not also assigned to the same stations in 2020. This makes the comparison of polling stations across time less reliable. Still, I estimate the following model to examine the effect of FRT on turnout at polling station locations:

$$Turnout_p = \beta_1 FRT_p + \beta_2 PostPeriod_t + \beta_2 FRT_p \times PostPeriod_t + \epsilon_p$$

$Turnout_p$ is the turnout at the polling station location p. For the 2019 general election turnout is calculated using one polling station and for the 2020 local election turnout is calculated from the two polling stations at one particular location. FRT_p is an indicator for if location p has any FRT (in either stations). $PostPeriod_t$ is an indicator for the 2020 local election (or the time, t, that is the post-period) when FRT was used.

The results are reported in Table A 7 and visualized in Figure A 7. FRT is associated with a 9.16 percentage point decrease in turnout for FRT stations; however this effect is not statistically significant at traditional levels (p=0.21).

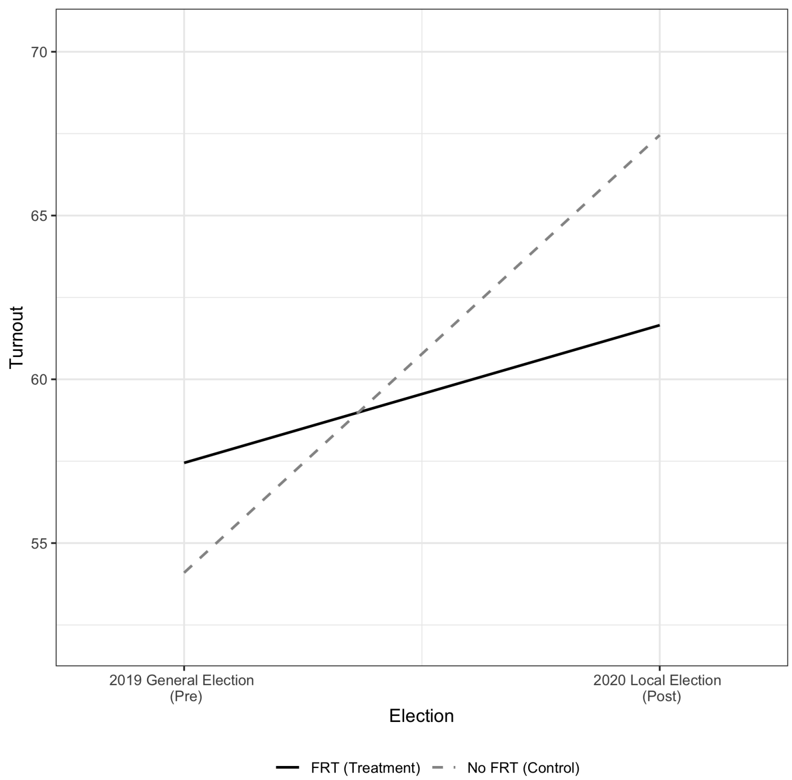
[2]The data from the previous local election for this municipality is not accessible because Kompally was previously a gram panchayat and TSEC does not have polling station level data from gram panchayats from the last election cycle.

Table A 7: Difference-in-Difference Effect of FRT on Turnout

	Dependent variable:
Facial Recognition Technology	3.35
	(3.08)
Post-Period (2020 Election)	13.36***
	(3.60)
FRT x Post	−9.16
	(7.19)
Observations	30

Notes: Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Figure A 7: Visual Representation of difference-in-difference analysis



A 3.7 Heterogeneous Effect of Percent Muslims

In this section, I detail the process for estimating the percent of Muslims in a polling station and present the regression results for the heterogeneous treatment effects of FRT by percent Muslim. The Indian census does not have religious demographics at the polling station level. To obtain estimates of the percent of Muslim voters assigned to each polling station I scrape voter rolls for all polling stations in Kompally and code a voter's religion based on their names. Each Kompally polling station has a public list of all citizens who are assigned to the particular station. The list provides the individuals full name and a second name of either their father or husband.[3] I use two approaches to code an individual's religion. The first approach uses an algorithm developed by Chaturvedi and Chaturvedi (2020). The algorithm uses character based machine learning models which learn character patterns to predict religion. The training data used in this classification approach comes from 115,000 names across 17 states along with 20,000 separate hand-coded names from Uttar Pradesh, a north Indian state. Because naming conventions vary by state in India and especially between north Indian and south Indian states, I use a second approach which entails the following steps. To code whether the individual is Muslim based on their name and their relative's name I take the following steps. First, I create a list of common male Muslim names for this region of India using the names of candidates for State Assembly or National Parliament races from 1962 to today for Telangana and Andhra Pradesh.[4]. This results in 518 unique Muslim first and last names[5]. Second, I carry out a process of coding an individual as Muslim if the individual's name *or* their relative name is one of the confirmed Muslim names. Only using confirmed male Muslim names does not prevent me from coding religion for female voters since I almost always have their male relative's names. For both approaches I then aggregate the number of Muslims to the polling station level to generate an estimate of the percent of Muslims assigned to the polling station. Both approaches are highly correlated ($correlation = 0.98$) so I opt for the character-based approach in the

[3]For about 5 individuals in each station they provided a mother's name instead of a father's or husband's name.

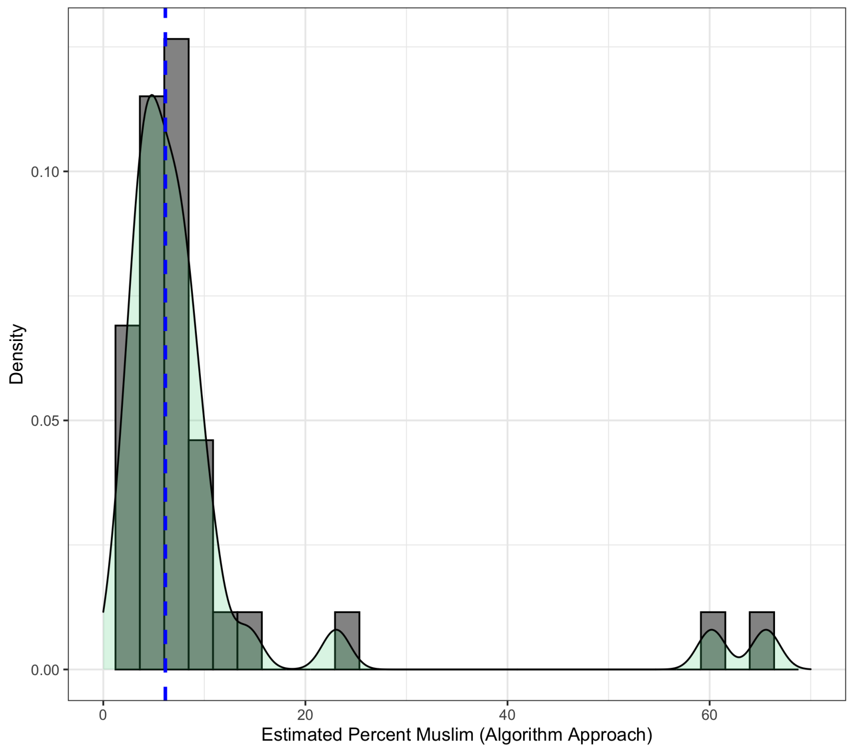
[4]I use Telangana and Andhra Pradesh since they were one state up until 2014. I use names of state and national candidates because the religion of these individuals were coded and verified using external sources by the Trivedi Centre for Political Data so they represent a list of *confirmed* Muslim names

[5]Some Muslim names in the list include *mohammed, nizamuddin, razak, rehman, hussain*

analysis.

Figure A 8 shows the distribution of the percent of Muslims in a polling station. The average percent of Muslims in Kompally municipality according the first approach is 10.69% and according to the second approach is 9.78%. The average percent of Muslims in Ranga Reddy (the district that Kompally belonged to in the 2011 Census) was 11.66%. This adds confidence in my estimates of the Muslim population in each Kompally polling station.

Figure A 8: Distribution of Percent Muslim Variable



The main text shows the marginal effect of FRT on turnout by the percent of Muslims in a polling station using the binning estimator. I also present regression results from a traditional interaction model. I calculate exact p-values by creating 100,000 randomly generated artificial treatment and control assignments while keeping the binary or continuous measure of Muslim population constant. This follows the recommendation from Caughey, Dafoe and Seawright (2017) to only permute units that are interchangeable under the null. In this case that is the FRT treatment but not the percent Muslim. Table A 8 and Table A 9 show the interaction effect of FRT and a continuous and binary measure of the percent of Muslims in a polling station respectively. While the results are negative, they are not statistically significant. I also subset to the 10 polling stations with FRT and examine the effect of the percent of Muslims in a polling station on turnout. These results, shown in Table A 10, indicate that among the stations with FRT, those with a higher share of Muslims has lower voter turnout. Increasing the percent of Muslims by 1 percentage point is associated with a 0.37 percentage point decrease in turnout. This means that increasing the percent of Muslims by one standard deviation (13.66 percentage points) is associated with a 5.02 percentage point decrease in turnout.

Table A 8: Heterogenous Treatment Effect of FRT on Turnout by Percent of Muslims (Continuous)

	Dependent variable:			
	(1)	(2)	(3)	(4)
Facial Recognition Technology	−0.53	−6.67	6.69	5.39
	(4.46)	(5.74)	(9.42)	(10.19)
	[0.92]	[0.24]	[0.45]	[0.54]
Percent Muslim	0.02	−0.29	0.02	−0.30
	(0.29)	(0.27)	(0.29)	(0.27)
	[0.99]	[0.94]	[0.92]	[0.16]
FRT x Percent Muslim	−0.39	−0.16	−2.02	−2.89
	(0.29)	(0.29)	(1.75)	(1.85)
	[0.40]	[0.58]	[0.16]	[0.03]**
Mean of DV	65.98	65.98	67.27	67.27
Election Controls	N	Y	N	Y
Polling Station Controls	N	Y	N	Y
Removed Outliers	N	N	Y	Y
Observations	36	36	34	34

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01. Models 3 and 4 remove the two outliers in the percent Muslim variable

Table A 9: Heterogenous Treatment Effect of FRT on Turnout by Percent of Muslims (Binary)

	Dependent variable:			
	(1)	(2)	(3)	(4)
Facial Recognition Technology	−4.76	−7.82	−4.76	−7.10
	(4.58)	(5.64)	(4.60)	(5.79)
	[0.33]	[0.15]	[0.36]	[0.23]
Above Median Percent Muslim	−5.48	−4.28	−5.48	−3.85
	(3.77)	(2.93)	(3.78)	(2.93)
	[0.67]	[0.71]	[0.23]	[0.25]
FRT x Above Median Percent Muslim	−6.65	−10.17	3.25	−1.51
	(7.78)	(8.97)	(6.64)	(8.17)
	[0.41]	[0.24]	[0.69]	[0.85]
Mean of DV	65.98	65.98	67.27	67.27
Election Controls	N	Y	N	Y
Polling Station Controls	N	Y	N	Y
Removed Outliers	N	N	Y	Y
Observations	36	36	34	34

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01. Models 3 and 4 remove the two outliers in the percent Muslim variable

Table A 10: Effect of Percent Muslim on Turnout among FRT stations

	Dependent variable:
Percent Muslim	-0.37^{***}
	(0.06)
Mean of DV	61.17
Observations	10

Notes: Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

A 3.8 Effect on Party Vote Share

In this section, I provide suggestive evidence that Muslim turnout decreased in FRT stations by looking at the party vote shares. The main parties contesting in the Kompally local body elections were the Telangana Rashtra Samithi (TRS), the Indian National Congress (INC), and the Bharatiya Janata Party (BJP). In past elections, such as the 2018 state assembly elections, the Muslim vote has generally been split between the TRS and the INC (or their grand alliance partners). This suggests that with fewer Muslims turning out to vote due to FRT, we should see decreased vote share for the INC and TRS and increase vote share for the BJP.

To examine how FRT affected party vote share, I move to the ward level (n=18) because I do not have party vote shares at the polling station level. I estimate the effect of having any FRT technology at the two polling stations for a ward. I only show results for the Telangana Rashtra Samithi (TRS), the Indian National Congress (INC), and the Bharatiya Janata Party (BJP). There were 2 candidates who ran with the Telugu Desam Party (TDP) and several who ran independently but they were not in all wards so the effects would be estimates for a very small sample size. Table A 11 shows the effect of FRT on the BJP, INC, and TRS vote shares. While the results are not statistically significant, the direction indicates that FRT may have reduced vote share for the TRS and the INC (who Muslims are likely to vote for) and slightly increased the vote share for the BJP (who Muslims are unlikely to vote for). This provides some additional suggestive evidence that Muslim turnout decreased due to FRT. Because of the small sample size, the standard errors are larger. Additional work with more polling stations would be required to confirm the effect of FRT on particular parties' vote shares.

Table A 11: Effect of FRT on Party Vote Shares

	Dependent variable:		
	BJP Vote Share	INC Vote Share	TRS Vote Share
	(1)	(2)	(3)
Facial Recognition Technology	4.20	−8.44	−8.03
	(9.17)	(9.23)	(6.42)
	[0.65]	[0.37]	[0.27]
Mean of DV	21.12	31.6	39.76
Observations	18	18	18

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01. The Facial Recognition Technology variable takes the value of 0 or 1 depending on if any polling station in the ward has FRT.

In addition to the above analysis, I also examine how FRT affected party vote share by aggregating to the ward level and conducting a difference-in-difference analysis. To so this I aggregate each polling station location to the ward level which is the level that I have information on the party vote share at (in the local elections, two polling stations make up a ward). I then match each vote share from the 2019 general election to a ward based on the polling station location. That provides 26 ward-level party vote share observations for 2019 and 2020. The weaknesses of this difference in difference approach comparing two different types of elections are discussed in Appendix A 3.6. I estimate the following model to examine the effect of FRT on vote share in wards:

$$PartyVoteShare_w = \beta_1 FRT_w + \beta_2 PostPeriod_t + \beta_2 FRT_w \times PostPeriod_t + \epsilon_w$$

$PartyVoteShare_p$ is the vote share for the BJP, INC or TRS in ward p. For the 2019 general election vote share is calculated using one polling station and for the 2020 local election vote share is calculated from the two polling stations at in a particular ward. FRT_w is an indicator for if ward w has any FRT (in either component stations). $PostPeriod_t$ is an indicator for the 2020 local election (or the time, t, that is the post-period) when FRT was used.

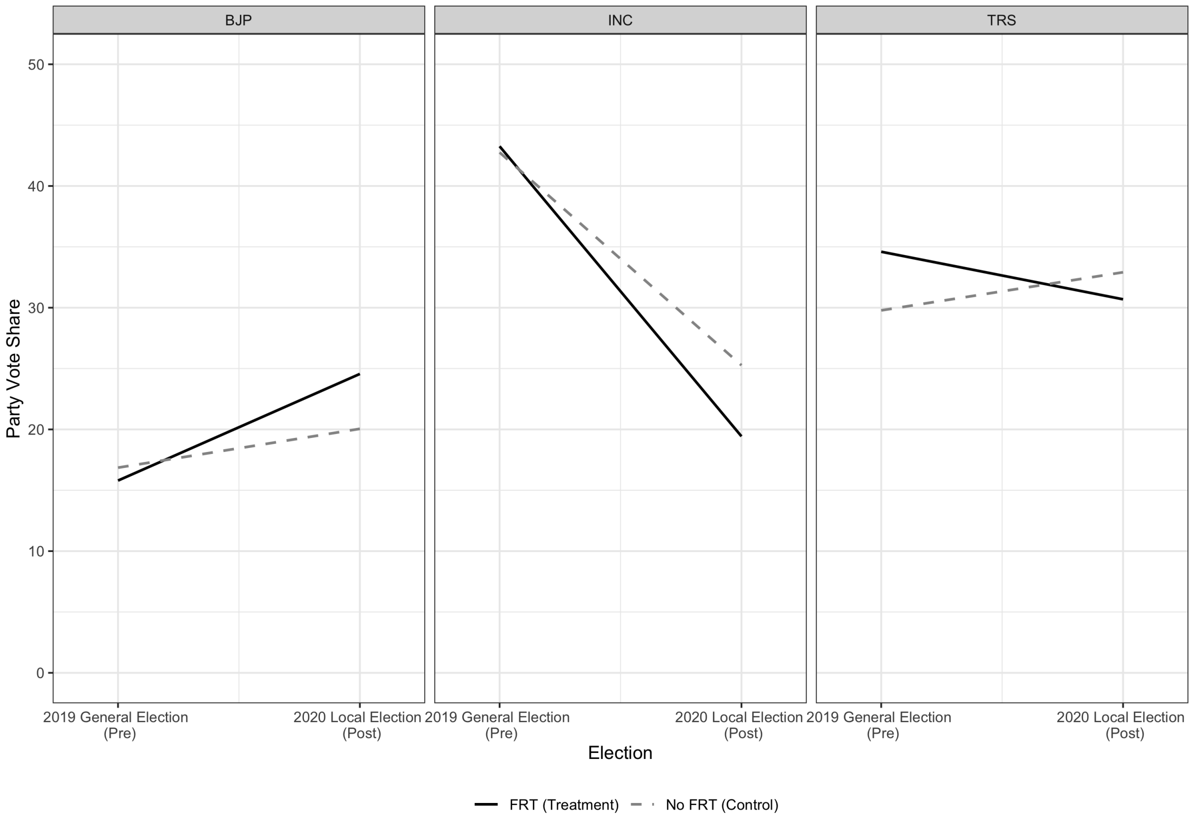
The results shown in Table A 12 and visualized in Figure A 9 indicate similar results to the analysis above. FRT has a positive relationship with BJP vote share and a negative relationship with INC and TRS vote share; however, these results are not statistically significant. Again, this necessitates further work to confirm whether FRT affects particular parties' vote shares.

Table A 12: Difference-in-Difference Effect of FRT on Voter Share for BJP, INC, and TRS

	Dependent variable:		
	BJP Vote Share	INC Vote Share	TRS Vote Share
	(1)	(2)	(3)
Facial Recognition Technology	−1.06	−1.48	2.50
	(2.88)	(3.59)	(5.15)
2020 Local Election	7.40	−10.96	5.45
	(6.61)	(7.27)	(4.96)
FRT x 2020 Local Election	1.37	−4.06	−9.36
	(12.93)	(12.62)	(8.36)
Mean of DV	20.44	38.19	34.16
Observations	26	26	26

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01. The Facial Recognition Technology variable takes the value of 0 or 1 depending on if any polling station in the ward has FRT.

Figure A 9: Visual Representation of difference in difference analysis of party vote share



A 3.9 Spillover Effects of FRT

The spillover of treatments across polling stations are common in elections (Ichino and Schündeln 2012; Neggers 2018). In this study, it is possible that polling stations without FRT that are located near stations with FRT may also be affected by FRT. First, there could be a lack of clarity among voters about which particular stations have FRT. This could lead a voter to not turn out to vote, thinking their stations will use FRT. Second, voters who intend to cast a fraudulent ballot by impersonating another individual on the voter roll could shift to a non-FRT nearby stations to vote so they could avoid the possibility of being discovered. This may lead to an increase in turnout at polling stations without FRT that are near FRT stations.

I study spillover effects by examining if polling stations without FRT that are located in the same physical location (e.g. school) as a polling station with FRT (or "near FRT stations") sees any differences in turnout. The results are shown in Table A 13. Model 1 tests the effect of near FRT stations on the full sample and Model 2 tests the effect of near FRT stations on only stations without FRT. The results do not a show a consistent or statistically significant effect of near FRT stations on turnout. This does not preclude FRT from having spillover effects, but in this pilot study, no evidence of spillovers is present.

Table A 13: Effect of Nearby FRT Station on Turnout

	DV: Turnout	
	(1)	(2)
Near FRT Station	2.44	-1.28
	(3.60)	(3.84)
	[0.5]	[0.75]
Mean of DV	65.98	67.83
Observations	36	26

Notes: Robust standard errors are reported in parentheses. Exact p-values are reported in brackets. *p<0.1; **p<0.05; ***p<0.01.

A 3.10 Evidence from Muslim Party Letter to TSEC

In this section, I provide suggestive evidence that Muslims would be especially concerned about FRT. After TSEC announced the use of FRT in elections, the All India Majlis-e-Ittehadul Muslimeen (AIMIM) party sent a letter to the election commission about the use of FRT in elections. The AIMIM party is a predominantly Muslim party headed by Hyderabad M.P. Asaduddin Owaisi. The party is often viewed as particularly representative of Muslim views and interests. The AIMIM also did not field any candidates in this municipality so the purpose of the letter was to voice concerns that their voters may have. I obtained a copy of this letter outlining the issues with FRT. A Member of the Legislative Council in Telangana from the AIMIM party wrote that FRT use in elections raised issues of privacy, legal consent, and photo misuse. The letter also emphasized apprehension about "the creation of a large database of facial contours and features" suggesting Muslim concern over this increase in state legibility through photos. Taken together, the letter suggests that Muslims more broadly were likely to disapprove of the use of FRT in polling stations.

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