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Ignorance is *Not* Bliss

EXPERIMENTAL EVIDENCE ON VOTER INFORMATION AND POLITICAL SELECTION IN INDIA

SIDDHARTH GEORGE, SARIKA GUPTA, YUSUF NEGGERS*

ABSTRACT

Nearly ten percent of Indian legislators face charges for violent crimes, and these legislators appear to have electoral advantages. We study why voters elect criminal politicians and test the role of information frictions by running a large-scale, mobile-based voter information campaign around the Uttar Pradesh state assembly elections. Over 450,000 voters across 3,500 randomly selected villages received voice calls and text messages informing them about the criminal charges of candidates in their constituency. Treatment increases votes for clean candidates and reduces votes for violent criminal candidates, with the strongest effects seen for the most violent crimes. Turnout remains unaffected.

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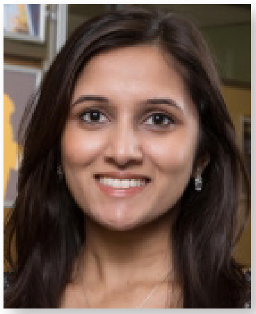

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INTRODUCTION

In recent years, adverse selection to political office has become a salient concern in many democracies. Brexit, the election of Donald Trump and growing support for populist and far-right leaders in Brazil, India, Turkey and many European countries has renewed interest in the frictions inherent in collective decisions. It has also sparked debate about the political impact of new media and communication technologies (Zhuravskaya et al. 2020). Understanding how to improve the screening function of elections may be particularly important for low-income democracies, where formal institutions impose fewer constraints on the in-office behavior of politicians.

In this paper, we study how information frictions affect voters' ability to evaluate and screen candidates and affect the quality of politicians who are elected. Specifically, we examine whether informing voters about candidates' criminal record affects their vote shares. We test this hypothesis by running a large-scale, mobile-based voter information campaign around a legislative election of an Indian state. Criminality is a serious problem in Indian politics. Approximately 34 percent of national legislators face criminal charges, and nine percent face charges for violent crimes such as murder, kidnapping, rape, extortion or armed robbery. Recent work suggests that criminal politicians are also bad for economic development: they reduce economic growth and increase poverty and crime in their constituencies (Prakash et al. 2019).

While there are many explanations for why voters may elect low-quality candidates to office, especially in contexts with pervasive ethnic voting [Banerjee and Pande, 2009] and vote-buying [Bratton, 2008, Vicente and Wantchekon, 2009], recent work has emphasized that information constraints also have an important role to play [Pande, 2011]. Specifically, poorly informed voters may lack the ability to effectively screen candidates, and in the absence of good information about quality, voters may rely on noisy signals about a candidate's distributive and policy preferences conveyed by her ethnicity or religion [Banerjee et al., 2012]. In addition, coordination failure amongst voters has also been discussed as one reason for poor political selection [Myerson, 1993, 1999], and low information levels may arguably exacerbate coordination problems.

Our experiment is designed to test whether better information can change political selection and the extent to which this information improves outcomes by helping voters break patterns of ethnic voting or coordinate their response to low quality candidates, i.e. criminals. We partnered with three major telecom companies in India, with a combined average census-village-level market share of 40 percent, to run a mobile-based information campaign in the run-up to the 2017 state assembly elections of Uttar Pradesh. We sent more than 450,000 mobile service subscribers living across roughly 3,500 villages text and voice messages, informing recipients about the characteristics of candidates in their constituency, randomizing at the village level. Each recipient received at least one voice message and text message two days before the election.

In control villages, citizens received no messages. In the treated villages, individuals received one of four different intervention messages depending on the group to which their village was randomly assigned. In a first group of treatment villages, individuals were given the *basic information message*, which urged recipients to get to know their candidates and think carefully before casting their vote, and additionally provides recipients with information on the number and types of criminal charges, if any, facing all of the major party candidates standing in their constituency. A second intervention group receives the *information plus coordination message,* which includes the basic information message plus content informing voters that many other citizens living in their area have received this same message. Finally, a third treatment group receives an *information plus ethnic-voting message* in which voters are provided criminality information and additionally urged to break the habit of voting along caste lines. The criminality information that is shared with voters is taken from a publicly available database of candidate affidavits that each candidate must file by law in order to contest in an Indian election. Our analysis also relies on polling station level electoral data, which closely aligns with village boundaries.

We find, pooling across the three information treatments, that voters respond to the information content of the messages. Clean candidates (who have no criminal record) receive a significant 2pp more votes in treated villages, while candidates with criminal charges receive fewer votes. Candidates with more charges face greater electoral penalties — approximately 0.9pp fewer votes per criminal charge — and murder charges see a 12pp reduction in votes. As a result, candidates with murder charges see a three-percentage point decline in their vote shares on average. Considering effects at the polling-station-level, the votes received by all "clean" candidates significantly increases by 2.5pp and those by criminal candidates declines, driven by candidates with murder-related charges. Overall, treatment increases the gap in votes earned by clean relative to criminal candidates by 8.8pp. Turnout is unaffected overall, but we are unable to determine the extent to which our treatment effects are driven by voters switching support for criminal to clean candidates, versus by different turnout changes by subsets of the electorate that offset each other.

Voters respond to the three information treatments — the pure information treatment, as well as the "coordination" and "ethnic voting" treatments — by switching away from criminal candidates and toward clean candidates. While the coefficients move in the same direction in each of the information treatments, the decline in vote share for candidates with murder charges and the increase in support for clean candidates is qualitatively larger in magnitude in the information treatment that include the coordination message. We cannot however reject that the treatment effects are identical at the five percent level.

Our findings contribute to a growing experimental literature that has shown moderately positive effects of voter information campaigns on electoral accountability and political selection [Pande, 2011]. We add to this literature by providing evidence of the importance of voter coordination and dismantling default decision-making as mechanisms through which information can affect these outcomes. These results contrast with an explanation for criminal politicians which argues that individuals may actually prefer criminals as they are better at providing private benefits and selective goods [Vaishnav, 2012]. Here, with better information, voters in aggregate switch away from criminals—reflecting some combination of changes in choice of candidate among voters and in who chooses to vote in the first place—in line with previous work from India which suggests that voters generally show an aversion to criminality or corruption [Banerjee et al., 2014].

Our work also builds upon existing work on voter information by evaluating an intervention that is easily scalable. It is difficult to scale insights from a majority of previous studies in developing countries because most experiments have been intensive, small-scale campaigns, often door-to-door or in village meetings. Scale is arguably best achieved via mobile-based interventions, given the high density of mobile phones in the developing world. While there is a growing literature on using mobile technology to encourage voter turnout before elections in rich countries [Dale and Strauss, 2009, Malhotra et al., 2011], we are only aware of two previous studies that have examined the effects of text messaging in the electoral setting in developing countries, both of which take place in sub-Saharan Africa [Aker et al., 2015, Marx et al., 2015]. In addition, both of these studies utilized mobile technology to help "get out the vote" whereas our experiment is unique in that we provided candidate-specific information with this technology aimed at affecting voter choice. By running our experiment in partnership with three large Indian telcos, we are able to reach high proportions of households in our treatment villages and can therefore better estimate the impact of voter information campaigns at scale.

The remainder of this paper is structured as follows. Section 2 provides a background on elections and politics in Uttar Pradesh, the setting for this experiment. Section 3 details the research design, data, and analysis plan, and Section 4 discusses the results of the experiment. Section 5 concludes and offers remarks regarding the cost-effectiveness and policy implications of this work.

BACKGROUND

Role of State Legislators

India is a federal parliamentary republic, with both national and state legislatures elected every five years on a rotating basis. Elected representatives in state assemblies are referred to as Members of the Legislative Assembly (MLAs), and they oversee single member constituencies after winning first-past-the-post elections. MLAs have many constitutionally sanctioned responsibilities, enjoy control over bureaucratic promotions and transfers (Iyer and Mani 2012), and play a significant role in resource allocation within their state and constituency. Thus, it is feasible that the quality of candidates elected to this position should matter for economic and development outcomes (Bhalotra et al. 2014).

Criminality in Indian Politics

Despite having a robust democracy — unlike many other developing countries, which have transitioned in and out of democratic rule over the past century — India has a serious problem with criminality in its political class. Political scientists largely argue that this weak political selection represents the consequence of deeper social and political forces, such as ethnic fractionalization (Chandra 2007). In areas with deep ethnic divisions, voters may actually see value in the "enforcer" credentials of criminal politicians and may choose to elect criminal politicians of their ethnic group to defend group interests (Vaishnav 2012). Nevertheless, other work has found significant negative economic and social consequences of criminal politicians governing an area. Prakash et. al (2019) find that MLAs facing criminal charges generate 22-percentage point lower economic activity than their non-criminal counterparts, and this result is especially driven by criminal politicians with violent charges. Chemin (2012) finds that crime is higher in criminal-ruled areas.

Uttar Pradesh

Our study focuses on the state assembly elections of Uttar Pradesh (UP), a state in Northern India. With a population of over 200 million, UP is the most populous state of India and the largest subnational unit in the world. It is also among the poorest states of India, with human development indicators similar to the level of Chad and a largely rural population. Still, following the trend across the developing world, India has seen an increase in mobile usage over the past several years, making mobile technology a feasible way to spread information widely in this context, even in rural areas.

UP has historically been rife with ethnic politics and political corruption. Politician quality is lowest in ethnically lop-sided constituencies, suggesting that voters may be trading off ethnic preferences for candidate quality (Banerjee and Pande 2009). Electoral participation of marginalized groups (e.g. women), who are arguably disproportionately affected by criminal politicians, is also low. For example, UP is ranked 32nd out of 35 states/territories in India in terms of female turnout.

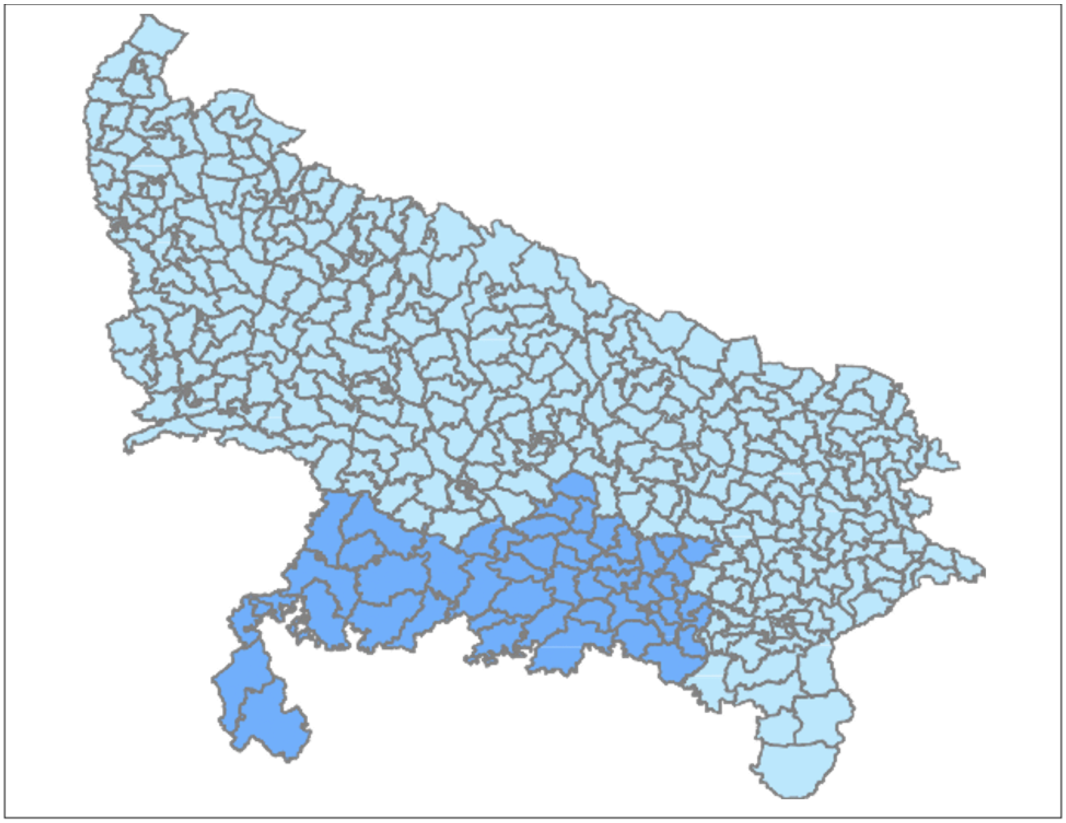
Given this political, economic and social backdrop, UP provides a good setting for testing a mobile-based information campaign aimed at increasing voter awareness of candidate criminality, allowing voters to better coordinate on their preferences and breaking default habits of ethnic voting.

Legislative Assembly Elections 2017

There were four main parties in the 2017 elections: (i) the *Bharatiya Janata Party* (BJP), who eventually won the election and controlled the federal government at the time; (ii) the *Samajwadi Party* (SP), who controlled the UP state government from 2012-17 and were therefore the incumbent party in the election; (iii) the *Indian National Congress* (INC), the principal opposition party in the country and (iv) the *Bahujan Samaj Party* (BSP), a party that primarily represents the interests of Dalit voters and ruled UP from 2007-12. The SP and INC formed an electoral alliance in the 2017 elections, so in most of the constituencies in our sample, there was only either an SP or an INC candidate but not both. Therefore, in practice, this election was a 3-party race, which resulted in some coordination issues for voters and created some prospect for strategic voting. This will be relevant to how to interpret our "Information plus Coordination" treatment.

Given the sheer size of the electorate in UP, elections take place in phases. In 2017, there were seven election phases, one every four days between February 11, 2017 – March 8, 2017. Each phase of the election covered 40-75 of the total 403 constituencies in UP. Our experiment was conducted around Phase 4 of the elections, and the map of included constituencies is shown in Figure 1. This election was a landslide victory for the BJP, who won 325 seats, representing over a three-fourths majority.

Figure 1: Experimental Constituencies in Uttar Pradesh



Source: Boston University Global Development Policy Center, 2021.

Notes: This figure shows the 49 assembly constituencies in Uttar Pradesh where we ran our mobile-based voter information campaign.

EXPERIMENT DESIGN

Intervention Structure

MESSAGE CONTENT AND EXECUTION

In order to carry out our intervention, we partnered with three major telecom companies in India: Idea, Airtel and Vodaphone. On average, the combined coverage rates (in terms of subscribers/ village population) of these three companies in the villages in our sample is 44 percent. For each treatment village, we blasted all mobile users with numbers registered to the given village jurisdiction under these telecom companies. The script of the voice message is longer and more detailed than that of the text message, but both convey similar information. Voice messages were recorded in Hindi, and text messages were sent in the Hindi language and Devanagari script.

It is common for citizens to receive information in the days leading up to an election from different parties and civil society groups. But all parties must strictly adhere to a freeze on campaigning that goes into effect one day before the election. To ensure that our messages were perceived differently from party-driven campaigning or propaganda, our messages explicitly noted that they were sent on behalf of our implementation partner, the Center for Governance and Development (CGD) in India, a non-profit, non-partisan political watchdog organization.

Villages that were assigned to the control group did not receive any voice or text message blasts. The remaining villages were randomly assigned to receive one of the following interventions:

2. Basic Information Message: This message contains the same content as the placebo message, but in addition provides detailed information regarding the criminal charges facing the major party candidates in the recipient's constituency. Below is an example of the content of this message for a constituency in which the major party candidates range from facing no criminal charges to facing serious violent charges:

> *"This message is from an unbiased, non-political NGO, Center for Governance and Development. Get to know your candidates correctly, and on Election Day, give your vote only after thinking carefully! In your area: 1. Madhusudan Kushwaha from BSP (elephant party) has one criminal case, with attempt to murder charges. 2. Prakash Dwivedi from BJP (lotus party) has no criminal cases. 3. Vivek Kumar Singh from Congress (hand party) has 3 criminal cases, but has no violent charges."*

As seen in the above example, the criminality information includes the name of the candidate, the name of the party he or she represents, the symbol associated with the given party, and the nature of pending criminal charges against the candidate, if any. When a candidate has any criminal charges, the number of charges is stated, followed by the specific charges for any violent crimes. If a candidate faces only non-violent criminal charges, after the number of charges, the message informs listeners that none of the charges are violent. If the candidate faces no criminal charges, the message informs listeners that the given candidate faces no criminal charges.

3. Information plus Coordination Message: This message has the same content as the basic information message but also emphasizes to listeners that the message has been shared widely to other individuals living in their area. This intervention is designed to test whether voters respond more strongly to information when they receive a public signal that allows them to coordinate their response with other voters. This message uses the following format:

"This message is from an unbiased non-political NGO, Center for Governance and Development, and many people in your area have already received it. Get to know your candidates correctly, and on Election Day, give your vote only after thinking carefully! In your area: <<Insert Criminality Information of Candidates>>. Now you can elect the right candidate with the people in your area.

4. Information plus Ethnic Voting Message: This message also builds upon the basic information message, but instead of adding the coordination element, it urges citizens to break the habit of ethnic voting. This intervention is designed to test whether criminality information is used more seriously to update voting behavior when it is coupled with a message that draws one's attention to flaws in default decision-making which are likely to undermine such information. Given the history of ethnic politics and voting in this context, this is an important channel to test or rule out when trying to understand how voters respond to information about candidate quality. This message contains the following:

"This message is from an unbiased, non-political NGO, Center for Governance and Development. Don't follow your old habits and vote only on the basis of caste or religion. Get to know your candidates correctly, and on Election Day, give your vote only after thinking carefully! In your area: <<Insert Criminality Information of Candidates>>."

In villages that were selected to receive any of the three candidate information interventions, individuals were sent one voice message and one text message with the corresponding information two days before the election.

Each of the three information interventions was sent to Vodaphone and Idea customers across about 430 villages. The next section provides details on the sampling and randomization.

SAMPLE SELECTION AND RANDOMIZATION

Phase 4 of the elections covered 11 districts containing 53 assembly constituencies (ACs). Due to the unavailability of reliable polling station location data, the two districts of Allahabad and Chitrakoot were excluded from our experiment, leaving an initial set of 39 ACs and 9,627 census villages. To avoid urban areas, where cross-contamination of treatment and control areas was a greater concern, and to improve our statistical power (by reducing the number of observations per treatment unit), we further restricted our sample to villages with between one and two polling stations. In addition, we excluded extremely large or small census villages from our sample, dropping villages in the top and bottom percentiles of the district-level distribution in terms of total population (corresponding roughly to populations below 150 and greater than 5,150). Finally, given that the delivery of our treatment relied on mobile phone possession, we also excluded villages in the bottom percentile in terms of village-level population share covered as Vodafone+Idea subscribers (corresponding to roughly a 10.6 percent coverage rate or lower). Together, these yield an experimental sample of 4,131 villages across 38 ACs.

We aimed to reach approximately 450,000 individuals with our messaging campaigns in Phase 4, allocated equally across the three candidate-information arms (basic information, information plus ethnic-voting, and information plus coordination), with the total number of treated individuals allocated across ACs in proportion to their populations. Villages were then randomly assigned across the four treatment arms and control, stratifying by: AC; number of polling stations contained within; above/below AC-level median Vodafone+Idea subscriber share of village population; and above/below AC-level median Vodafone+Idea number of subscribers.

Data

This analysis relies on several sources of data. The candidate criminality information that is inserted in the voice and text messages and used in the subsequent analysis comes from publicly available candidate affidavits filed with the Election Commission of India. In 2003, the Indian Supreme Court made it mandatory for all candidates to the national or state legislative bodies of India to file sworn affidavits which provide details of their education, assets, liabilities, and criminal convictions or charges. Given strict penalties for lying and strong incentives for opposition parties or media to uncover such lies, misreporting in such affidavits is considered to be minimal [Prakash et al., 2015].

As these affidavits are only filed during the nomination period (roughly 15-19 days before the election), we had a very short window of time to turn the data around to share with our telecom partners in order to blast the information to citizens before the elections. Therefore, we did not wait for the information to be summarized online and instead manually gleaned the information from each individual affidavit for all of the major party candidates standing for election in the constituencies selected for this study.

For demographic information about the villages in our sample, we used data from the 2011 Indian National Census. This dataset provided us with population numbers, caste composition, literacy rates, gender composition, land area and land usage patterns for each village. In addition, we used 2011 census village shapefiles acquired from ML InfoMap together with polling station GPS coordinates from the dataset of Susewind (2014), which allowed us to spatially match polling stations to census villages in order to conduct the polling-station- and polling-station-by-candidate-level analyses of our results.

Polling-station level electoral data is publicly available from the website of the Uttar Pradesh Office of the Chief Electoral Officer (CEO). This includes the total turnout in each polling station as well as turnout by gender. It also shows the total number of registered voters (referred to as "electors") in each polling station and the number of votes given to each candidate. We also compile historical data on vote shares in past elections to use as predictors of the 2017 UP election outcomes.

Finally, our telecom partners provided us with data on their mobile coverage rates in the villages covered in this study as well as pick-up rates and duration of listening rates for the voice messages that we sent. This data will be used to calculate various measures of treatment intensity in future analysis.

Descriptive Statistics

PREVALENCE OF CRIMINAL POLITICIANS

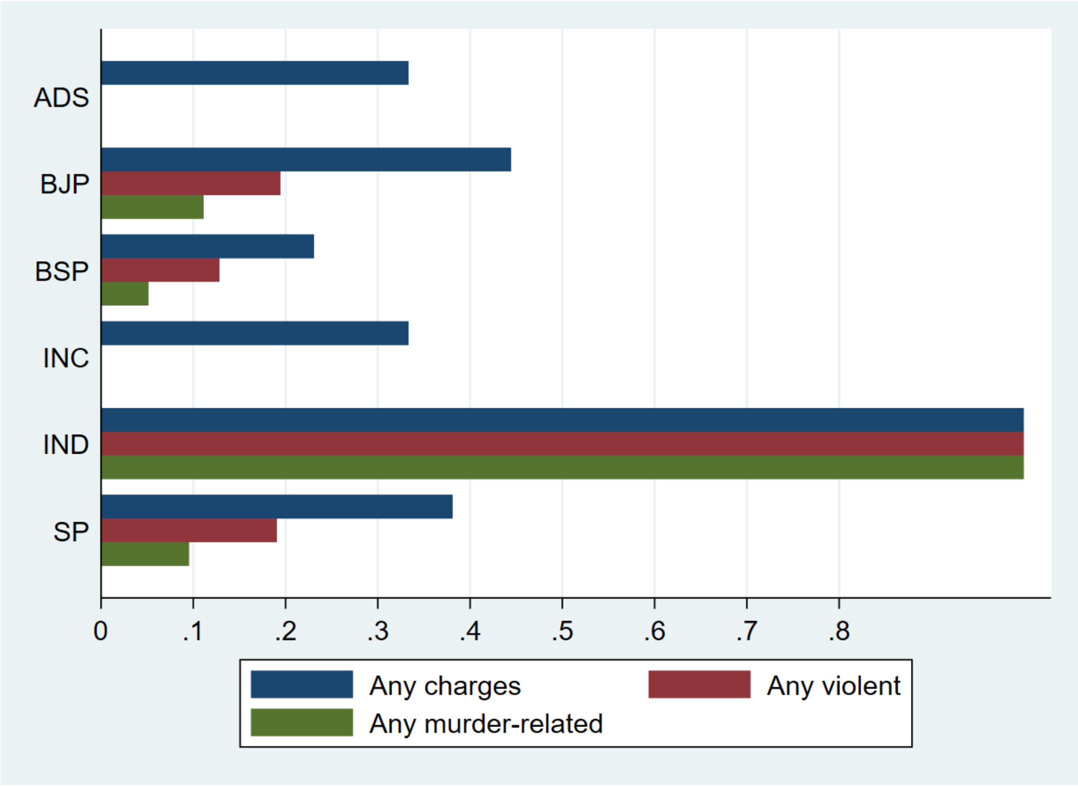
As in other states, a high share of major party candidates in our sample have criminal charges. Table 1 shows that, of the 119 major party candidates standing for election in the 38 constituencies targeted with our interventions — these were all the constituencies who voted in Phase 4 of the elections — nearly 35 percent have a criminal charge. Moreover, over 40 percent of these criminal politicians face charges — or 15 percent of all major party candidates — face charges for violent crimes. And a full quarter of criminal politicians — eight percent of all major party candidates — face charges for murder or attempt to murder.

Table 1: Prevalence of criminal charges among major-party candidates

	Mean	Obs.
	(1)	(2)
A. Candidate level		
Criminal charge	0.352	119
Violent charge	0.151	119
Murder-related charge	0.084	119
B. Constituency level		
Any charge	0.795	39
Any violent charge	0.436	39
Any murder-related charge	0.256	39

Notes: Panel A presents the share of major-party candidates facing criminal charges of each type in the 39 assembly constituencies covered by our study in phase 4 of the 2017 state assembly election in Uttar Pradesh. Panel B presents the share of these assembly constituencies with at least one candidate facing a criminal charge of each type.

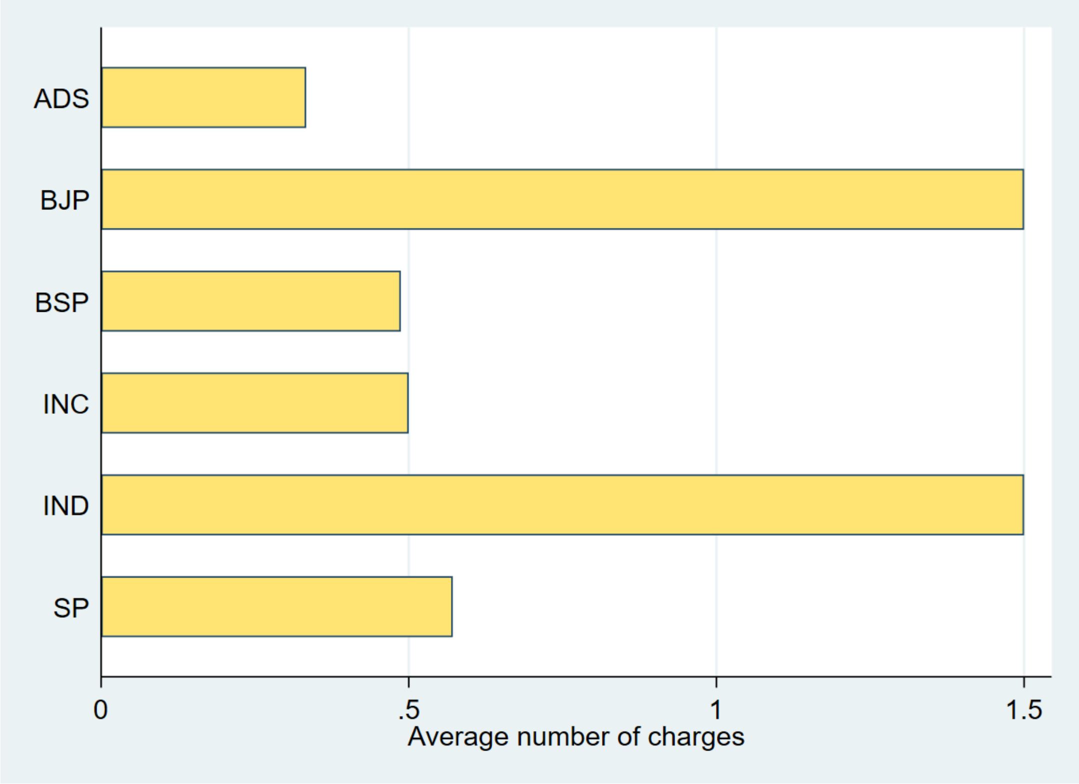
Figure 2a: Criminal Charges by Candidate Party – Type



Source: Boston University Global Development Policy Center, 2021.

Notes: This figure presents the distribution of candidates with criminal charges by party and by type of charge. Violent crimes refer to murder, attempt to murder, rape, kidnapping, extortion and armed robbery.

Figure 2b: Criminal Charges by Candidate Party – Number



Source: Boston University Global Development Policy Center, 2021.

Notes: This figure presents summary statistics on the average number of charge per candidate by party for the major parties contesting in the 2017 UP state assembly elections. ADS refer to the Apne Dal (Sonelal), BJP refers to the Bharatiya Janata Party, BSP refers to the Bahujan Samaj Party, INC refers to the Indian National Congress, IND refers to Independent candidates, SP refers to the Samajwadi Party.

DISTRIBUTION OF CRIMINAL POLITICIANS

A high share of criminal candidates raises the question of how widely they are dispersed. On the one hand, criminal politicians could be concentrated in a handful of "bad places," where ethnic divisions are rife and criminal politicians help enforce their group's private interests. This would be the prediction of theories that believe weak states, lawlessness and other place-specific features explain voters' demand for criminal politicians. By contrast, what we see in Table 1 demonstrates that criminal candidates are quite geographically dispersed. There is at least one criminal candidate from a major party in 80 percent of constituencies and a major party candidate with a violent charge in 44 percent of constituencies. But these constituencies do not seem to be "bad places" where only criminals enter politics: in fact, only in six percent of constituencies are all the major party candidates criminals, and there is no constituency where all are violent. In other words, the vast majority of electoral races (74 percent) feature both a criminal and a clean candidate. One would expect the effect of our information campaign to be particularly strong in these areas.

RELATIONSHIP BETWEEN CRIMINAL STATUS AND ELECTORAL PERFORMANCE

We confirm the association between criminal status and electoral performance that other authors (notably Vaishnav 2017) have documented. The results are shown in Table 2. As seen in Column 1, criminal candidates on average receive a 7.8pp higher vote share than non-criminal candidates. The inclusion of party fixed effects reduces this coefficient to 4pp but does not eliminate the relationship.

Columns 3 and 4 demonstrate that the strong electoral performance of criminal candidates is driven by those with violent criminal charges. Violent criminals earn 11pp more votes than clean candidates, and this coefficient is 5.1pp even after the inclusion of party FE. The reduction in the magnitude of the point estimate as party FE are added suggests that there is sorting, and in particular, that criminal candidates are more likely to get tickets from popular parties.

Table 2: Electoral Advantage for Criminals?

	Dependent variable: Vote share			
	(1)	(2)	(3)	(4)
Any criminal charge	0.0788***	0.0401**		
	(0.0280)	(0.0169)		
Nonviolent criminal charge			0.0486	0.0311
			(0.0290)	(0.0210)
Violent criminal charge			0.110**	0.0507**
			(0.0408)	(0.0240)
Years of Education (SHRUG)	0.00798**	0.00376	0.00778**	0.00374
	(0.00320)	(0.00275)	(0.00326)	(0.00276)
Log (electors)	-0.00243*	-0.00233*	-0.00243*	-0.00233*
	(0.00131)	(0.00131)	(0.00131)	(0.00131)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.178	0.303	0.185	0.303
Observations	9077	9077	9077	9077

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Notes: This table shows results from polling-station-by-candidate-level regressions of vote share on criminality in the control group from Phase 4 of the UP State Assembly Elections of 2017. In Columns 1 and 2, Criminal is a dummy that takes the value of 1 if the candidate faces any criminal charges, regardless of type. In Columns 3 and 4, Non-Violent is a dummy variable that takes a value of 1 if the candidate faces charges that are all non-violent, and Violent is dummy variable that takes a value of 1 if the candidate faces at least 1 violent criminal charge. All regressions include controls for log total population, share female, share SC/ST, share literate, log number of registered voters, and constituency fixed-effects. Columns 2 and 4 also include party fixed-effects. Standard errors, clustered at the village and candidate level, are shown in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Empirical Strategy

Given the randomized assignment of treatment status, our core empirical strategy is straightforward. We first examine the electoral impacts of the information campaigns on candidates of different types, estimating the following polling-station-by-candidate-level regressions:

$$Y_{cpva} = \alpha_a + \beta Info_{va} + \theta Crim_{ca} + \varphi\,(Info_{va} * Crim_{ca}) + \mathbf{X_{pva}}\lambda + {}_{cpva}. \quad (1)$$

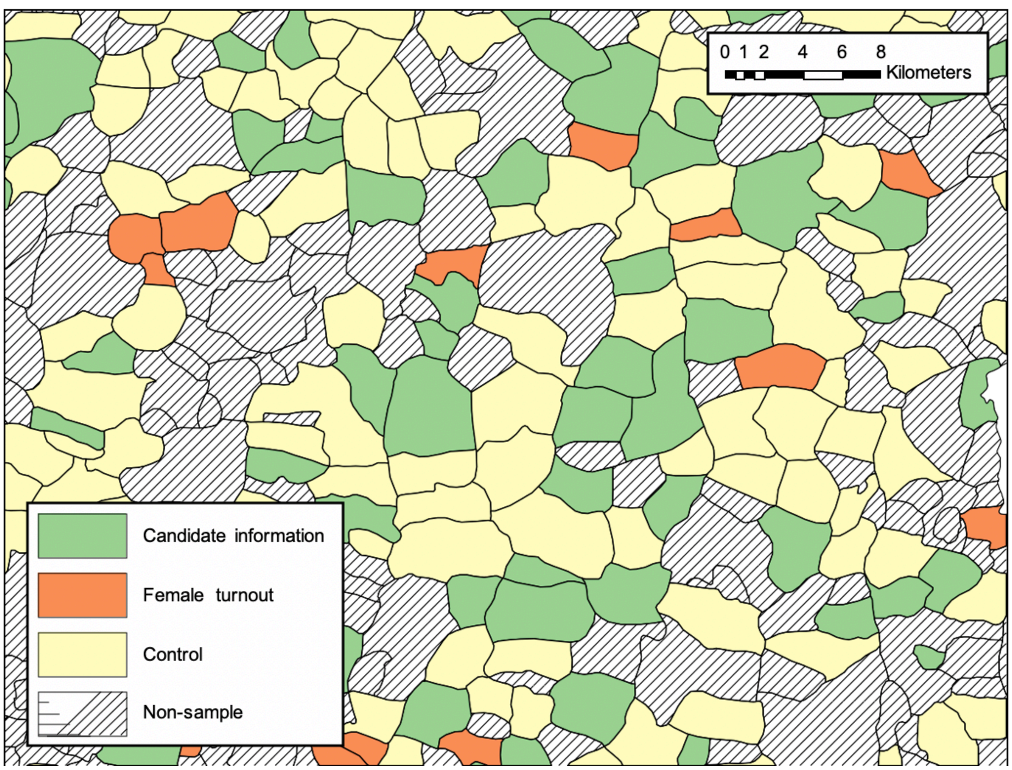
Y_{cpva} is a voting outcome (vote share or log votes) for candidate c at polling station p in census village v in assembly constituency a, $Crim_{ca}$ is an indicator taking value 1 if a candidate has any criminal charges and 0 otherwise, and α_a are assembly constituency fixed effects. $Info_{va}$ is an indicator for whether subscribers in a given village received any of the information treatments (basic information, information plus ethnic-voting, information plus coordination). The set of additional controls, $\mathbf{X}$, includes village-level characteristics (log population, share female, share literate), the log number of registered voters at the polling station, and fixed effects for the remaining randomization strata (number of polling stations contained within; above/below AC-level median Vodafone+Idea subscriber share of population; and above/below AC-level median Vodafone+Idea number of subscribers). Standard errors are clustered by both village and candidate. We exclude the sample of villages receiving the women's mobilization treatment from this analysis. As robustness checks, we also consider versions of this specification which additionally include party fixed effects or replace the assembly constituency fixed effects with candidate fixed effects (which are equivalent to assembly-constituency-by-party fixed effects).

In the above regression, β gives the average effect of receiving any of the information treatments for candidates with no criminal charges, and φ gives the marginal effect of treatment for criminally charged candidates. We also consider a specification that allows for heterogeneity in impacts by the different information treatments, where we replace the combined candidate-information-campaign indicator in equation 1 with three separate dummies corresponding to inclusion in each arm of the information intervention. Further, we allow for heterogeneity in treatment effects by severity of criminal charges, replacing the criminality dummy with a set of indicator variables capturing into which of a set of mutually exclusive categories of most-severe charge types each candidate falls: non-murder-related, attempted murder, and murder.

When considering the potential effects of the candidate information treatments on outcomes at the polling-station level, we use specifications of the form:

$$Y_{pva} = \alpha_a + \beta Info_{va} + \mathbf{X_{pva}}\lambda + {}_{pva}. \qquad (2)$$

Figure 3: Example Variation in Randomized Village Treatment Status



Source: Boston University Global Development Policy Center, 2021.

Notes: This figure illustrates the variation in exposure to information campaigns induced by our experiment.

Here, the outcome of interest is a voting-related outcome at polling station p in village v, and *Info* can be either a single indicator variable for any information treatment or a vector of three indicators corresponding to the three different information treatment arms. Standard errors are clustered by census village.

Balance Tests

To validate our randomization protocol, we follow the standard approach of testing for balance in a set of observable pre-election economic and political characteristics across our treatment and control villages. Specifically, we estimate our preferred polling-station level specification above (i.e., 2), and present coefficients from a regression of each village- level characteristic on a set of treatment dummies and the set of randomizations strata. As demonstrated in Table 3, we consider balance on the following economic variables: total population, female population share, SC/ST population share, literacy rate, and Vodafone/Idea subscriber share of population. We also show balance on the following political characteristics: electorate size, and vote shares that each major party achieved in that polling station in the 2014 national legislative elections, which was the most recent prior election. Out of 33 comparisons, equality can be rejected at the ten percent level or below in only one. This provides strong evidence that our information treatment was balanced, and the following results indicate the effect of the campaign rather than other unobserved heterogeneity between treated and control villages.

Table 3: Balance check

	Control	Basic Info	Info+Coord	Info+Ethnic	P-values of difference		
	(1)	(2)	(3)	(4)	(2)-(1)	(3)-(1)	(4)-(1)
Panel A: Village level							
Log (Total Pop)	7.165	7.177	7.173	7.149	0.999	0.708	0.999
	(0.624)	(0.627)	(0.617)	(0.634)			
Share female	0.478	0.478	0.478	0.478	0.715	0.990	0.738
	(0.023)	(0.022)	(0.025)	(0.024)			
Share literate	0.566	0.570	0.571	0.571	0.150	0.303	0.204
	(0.087)	(0.083)	(0.082)	(0.082)			
Share SC/ST	0.284	0.294	0.289	0.291	0.136	0.631	0.453
	(0.157)	(0.148)	(0.146)	(0.143)			
Vodafone/Idea pop share	0.158	0.173	0.172	0.172	0.396	0.278	0.292
	(0.037)	(0.026)	(0.025)	(0.027)			
Panel B: Polling station level							
Log (electorate size)	6.752	6.773	6.743	6.778	0.290	0.569	0.110
	(0.368)	(0.377)	(0.363)	(0.345)			
Log (BSP votes in 2014)	4.401	4.423	4.397	4.411	0.676	0.601	0.906
	(0.963)	(0.944)	(0.988)	(0.917)			
Log (INC votes in 2014)	3.317	3.362	3.322	3.302	0.618	0.595	0.945
	(1.409)	(1.393)	(1.399)	(1.430)			

(continued)

Table 3: Balance check (cont.)

	Control	Basic Info	Info+Coord	Info+Ethnic	P-values of difference		
Log (SP votes in 2014)	4.359	4.339	4.329	4.469	0.507	0.831	0.010
	(1.056)	(1.091)	(1.054)	(1.023)			
Log (BJP votes in 2014)	5.135	5.166	5.190	5.096	0.543	0.116	0.206
	(0.800)	(0.779)	(0.778)	(0.817)			
Log (winner votes in 2014)	5.297	5.310	5.334	5.278	0.962	0.486	0.633
	(0.720)	(0.718)	(0.724)	(0.735)			
Observations	2223	440	428	420			

Notes: This table compares average characteristics of all of the villages in our sample across the control and treatment groups. Columns 1 – 4 show the means and standard deviations for the following villages: (1) control group, (2) basic information message group, (3) information plus coordination message group, (4) information plus ethnic voting message group, respectively. The remaining colums report the coefficients from an OLS regression of the listed outcome on a dummy treatment indicator. Constituency fixed effects are included in this regression but no other controls. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

RESULTS

Effect of Voter Information Campaign on Electoral Outcomes

BASELINE RESULTS

Our key outcome of interest is whether clean candidates (i.e. with no criminal charges) earn more votes and criminal candidates earn fewer votes, when voters are informed about the charges of all candidates standing for election in their constituency. Table 4 presents our baseline results from estimating equation 1, showing how the polling-station-by-candidate- level votes received by candidates with different criminal backgrounds changed as a result of the information interventions. In columns 1 and 2, the outcome is log (votes received) whereas in columns 3 and 4, the outcome is vote share. We pool across all three interventions that provided criminality information (we will explore heterogeneity in Table 7). We begin, in Panel A, by showing results where we assume that treatment effects are similar for all criminal candidates (e.g. similar electoral penalty of revealing criminal status for those with one vs ten charges and both white-collar criminals and murderers). Column 1 shows that, in treated villages, clean candidates received 2.5pp more votes (significant at the five percent level) while criminal candidates received fewer votes, though this result is not significant. Column 2 shows that replacing constituency fixed effects with the more restrictive candidate fixed effects leaves our results virtually unchanged. Turning to vote shares, we see (in columns 3 and 4) that treatment had no impact on average vote shares for either clean or criminal candidates. We will discuss whether treatment-induced turnout responses can explain this difference when we examine how treatment affected polling-station level outcomes in the next section.

TREATMENT EFFECT HETEROGENEITY BY NUMBER OF CRIMINAL CHARGES

In Panel B, we explore whether the electoral effects of the information campaign were larger for candidates with more criminal charges. The results in columns 1 and 2 show that the electoral benefit to clean candidates is about the same (roughly 2.4pp more votes) but criminal candidates face an electoral penalty of 0.9pp votes per charge. This reduces the apparent electoral premium that criminal charges earn (estimated using a naive regression of votes on charges) by about 15 percent.

Table 4: Baseline Results: Effect of Voter Information Campaign on Electoral Performance

	Dependent variable: Vote share			
	(1)	(2)	(3)	(4)
Panel A: Pooling all criminal candidates				
Info treatment	0.025**	0.024**	0.002	0.002
	(0.012)	(0.012)	(0.002)	(0.002)
Info*Criminal candidate	-0.032	-0.032	-0.004	-0.003
	(0.032)	(0.028)	(0.007)	(0.006)
Fixed effects	Constituency	Candidate	Constituency	Candidate
Adjusted R^2	0.255	0.456	0.149	0.409
Observations	15522	15522	15534	15534
Panel B: Heterogeneity by number of criminal charges				
Info treatment	0.021**	0.022**	0.002*	0.003
	(0.010)	(0.010)	(0.001)	(0.002)
Info*Number of charges	-0.009*	-0.009**	-0.001	-0.002
	(0.004)	(0.004)	(0.001)	(0.001)
Fixed effects	Constituency	Candidate	Constituency	Candidate
Adjusted R^2	0.247	0.456	0.100	0.407
Observations	15522	15522	15534	15534
Panel C: Heterogeneity by severity of criminal charges				
Info treatment	0.024*	0.024**	0.002	0.002
	(0.013)	(0.012)	(0.003)	(0.002)
Info*Non-murder crim	-0.011	-0.012	0.001	-0.000
	(0.032)	(0.029)	(0.007)	(0.007)
Info*Attempt to murder	-0.070	-0.065	-0.007	-0.007
	(0.057)	(0.051)	(0.016)	(0.017)
Info*Murder	-0.123***	-0.120**	-0.028***	-0.025***
	(0.044)	(0.049)	(0.009)	(0.009)
Fixed effects	Constituency	Candidate	Constituency	Candidate
Adjusted R^2	0.255	0.456	0.152	0.402
Observations	15522	15522	15534	15534

Standard errors, clustered at the village and candidate level, are in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

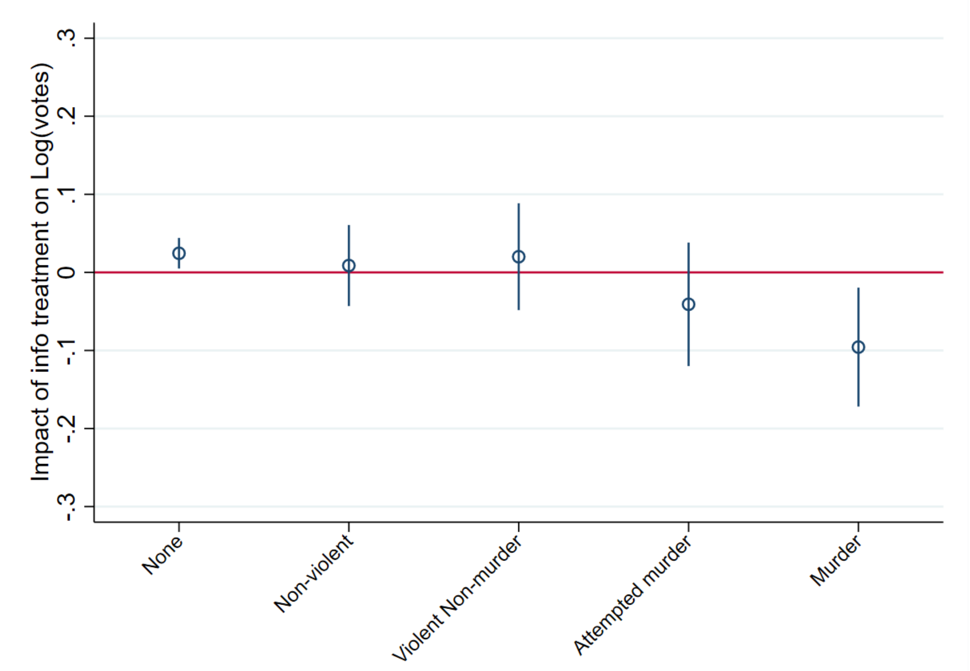
The average criminal candidate (who has about 2.5 charges) thus loses about 2.2pp votes. Columns 3 and 4 show a qualitatively similar pattern of results — raising the vote shares of clean candidates and lowering the votes shares of, but with weaker statistical significance. The information treatment raises the vote shares of clean candidates by 0.1pp and imposes a vote share penalty of 0.1pp per criminal charge, but this latter result is not statistically significant.

HETEROGENEITY BY TYPE OF CRIME

When we relax the assumption that criminal candidates are affected similarly and explore differential treatment effects by type of criminal charge, we see that the electoral penalty of informing voters about criminal status increases with the severity of the crime. Panel C explores heterogeneity by the severity of the criminal charge. In columns 1 and 2, we see that the electoral penalties of information disclosure are particularly severe for criminal politicians with the most severe charges. Candidates with non-violent charges have a negligible electoral penalty, while candidates with attempt to murder charges (who represent a major party in roughly 12 percent of elections) earn 6.5pp fewer votes when information is disclosed, though this effect is not significant. The largest and electoral effects are felt by politicians with the most severe charges (i.e., murder), who earn 12pp fewer votes in treated polling stations, an effect which is significant at the five percent level.

Columns 3 and 4 of Panel C in Table 4 depict the effects of treatment on vote shares. Murderers (who are present in 13 percent of the sample) only group of candidates who lose significant vote share (2.5pp) due to the information campaign. Figure 4 presents the results graphically, demonstrating a clear monotonic relationship between charge severity and electoral penalty of informing voters.

Figure 4: Treatment Effect by Type of Crime



Source: Boston University Global Development Policy Center, 2021.

Notes: This figure presents coefficients from the following regression: $Y_{cpva} = \alpha_a + \beta Info_{va} + \theta Crim_{ca} + \varphi\ (Info_{va} * Crim_{ca}) + \mathbf{X}'_{\mathbf{pva}}\lambda + e_{cpva}$. We show $\beta + \varphi$ separately by type of candidate crime.

HETEROGENEITY BY COMPOSITION OF CANDIDATES IN ELECTION

The interaction with multiple sub-groups necessarily reduces power to reject equality of coefficients, but it is still the case that the equality of the treatment effects for candidates with the least and most severe patterns of charges revealed can be rejected. In Table 5, we examine heterogeneity by the composition of candidates contesting the election. This is an important measure over which to consider heterogeneity because voters may be comparing candidates, and the effect of information about candidates' criminal charges will depend on the *relative* criminal status of each candidate in addition to their *absolute* criminal status. The results broadly show that the overall effects are driven by elections where a violent criminal candidate is present. Panel A shows that in such elections, the information campaign led to clean candidates gaining 8.5pp more votes and 1.1pp higher vote share. Criminal candidates get 12.9pp fewer votes and a 2.2pp lower vote share (though this latter result is not statistically significant). By contrast, in elections where there is no violent criminal, treatment has no impact on votes received and vote shares.

Table 5: Heterogeneity by Composition of Candidates in Election

	Elections with a violent criminal		Elections with no violent criminal	
	Log (votes)	Vote share	Log (votes)	Vote share
Panel A: Pooling all criminal candidates				
Info treatment	0.085***	0.011*	0.007	-0.001
	(0.029)	(0.006)	(0.012)	(0.002)
Info*Criminal candidate	-0.129**	-0.022	0.005	0.004
	(0.058)	(0.014)	(0.032)	(0.007)
Fixed effects	Candidate	Candidate	Candidate	Candidate
Adjusted R^2	0.489	0.441	0.441	0.396
Observations	4135	4141	11387	11393
Panel B: Treatments effects by type of crime				
Info treatment	0.085***	0.010*	0.007	-0.001
	(0.029)	(0.005)	(0.012)	(0.002)
Info*Non-murder crim	-0.073	-0.012	0.005	0.004
	(0.064)	(0.014)	(0.032)	(0.007)
Info*Attempt to murder	-0.123*	-0.015		
	(0.063)	(0.020)		
Info*Murder	-0.178**	-0.033**		
	(0.066)	(0.013)		
Fixed effects	Candidate	Candidate	Candidate	Candidate
Adjusted R^2	0.489	0.435	0.441	0.396
Observations	4135	4141	11387	11393

Standard errors, clustered at the village and candidate level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B investigates treatment effects by type of crime. Consistent with Panel C of Table 4, murder candidates experience the worst electoral penalty — they get 17.8pp fewer votes and have a 3.3pp lower vote share. Again, we see that treatment causes no changes in electoral performance in races without a violent candidate.

Thus far, we have provided evidence that criminal candidates were punished by voters as a result of our information-based treatments, with those facing the most and the most serious criminal charges experiencing the largest penalty at the ballot box. Clean candidates benefit from our information campaign, and benefit when facing at least one other violently-charged candidate.

TURNOUT & OTHER POLLING-STATION LEVEL OUTCOMES

In Table 6, we examine the impact of the pooled information treatment on polling-station level combined voting for candidates of different types and overall turnout.

Table 6: Station-level voting impacts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (clean vote)	Clean VS	Log (crim votes)	Crim VS	Log (murd votes)	Murder VS	Clean-Crim vote gap	Clean-Crim margin
Panel A: Polling-station level electoral performance								
Info treatment	0.025	0.006	-0.019	-0.005	-0.070	-0.018*	0.088**	0.014
	(0.016)	(0.005)	(0.021)	(0.006)	(0.044)	(0.010)	(0.042)	(0.011)
Adjusted R^2	0.727	0.756	0.575	0.649	0.399	0.357	0.243	0.624
Observations	4942	4950	3965	3973	1332	1336	2069	3825
Panel B: Turnout effects								
	Log (turnout)	Log (male turnout)	Log (female turnout)					
Info treatment	0.006	0.006	0.005					
	(0.005)	(0.005)	(0.005)					
	0.837	0.835	0.820					
	5090	4984	4985					

Standard errors, clustered at the village level, are in parentheses. All regressions include constituency fixed effects.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Panel A considers a set of polling station level electoral outcomes. Mirroring the candidate-by-station-level results, we observe that total votes across all candidates without any criminal charges increase by an average of 2.5pp (p-val=0.102). The vote shares of criminal candidates do not change on average, but they (again mirroring the results of Table 4), candidates with murder charges receive substantially fewer votes and vote shares. This results in an increased gap between the number of votes earned by the clean and criminal candidates (8.8 percent on average).

Panel B examines turnout effects. We see relatively muted turnout effects on the whole, on the order of 0.6pp. Of course, treatment could affect turnout differentially for different subsets of the electorate. For example, some voters may have previously believed that there are few significant differences between the candidates and may have been unwilling to incur the cost of voting. The information treatment may change their beliefs and increase turnout amongst this group. On the other hand, supporters of the criminal candidate's party may now update downwards about the benefits of voting for their party and be nudged by the information treatment to stay home. Both these effects might well be larger when a candidate with murder charges is in the race. Thus, the pattern of results we identify could be driven by vote switching, offsetting turnout changes or some combination of the two, and we are not able to separately identify which forces are driving the bulk of the treatment effect.

INTERPRETATION

Overall, the results presented in Tables 4-6 suggest that the criminality information pro- vided to voters in our interventions was useful to them and influenced their voting decisions. This supports the notion that baseline knowledge levels of candidate quality may be low, in line with previous research conducted in India which suggests voters do update and make sophisticated voting decisions when more information on candidates is made avail- able [Banerjee et al., 2011]. We contribute to this literature by showing that even one-time, easily scalable, mobile-based interventions can achieve substantial impact by moving votes away from those with the most severe criminal charges. In addition, the pattern of results we observe suggests that our information treatments did not generally cause disillusionment and depress turnout, as was the case in Mexico when corruption information was publicized a week before the 2009 municipal elections [Chong et al., 2015]. In the analysis in this section, we have pooled across all three of the information interventions. To provide additional insight into the mechanisms underlying the treatment effects, the next section considers whether there are differential impacts by type of information message provided.

Heterogeneity by type of message: the impact of coordination

Our interventions included three informational treatments. One provided only basic in- formation on candidate criminality, while the others combined this basic information with other messaging aimed at either: providing a public signal to voters that many other voters had also received the information about candidate criminality or urging citizens to break the habit of ethnic voting.

Table 7 presents results. We show the impact of each information treatment on polling station level vote shares of major party candidates. In columns 1 and 2 of Table 7, we see that the basic information message increases votes of clean candidates by 2.6pp while the coordination plus increases votes for clean candidates by 2.1. Moreover, treatment effects on clean candidates are not significantly different between the two messages. However, the coordination message is able to engender a larger punitive response from voters. Candidates with murder-related charges lose 11.6pp votes (significant at the five percent level) and 2.8pp vote share when voters are exposed to the coordination message. By contrast, the basic information message reduces the votes earned by murder-related candidates a statistically insignificant 9pp and has no impact on vote shares. We are however generally unable to reject that the treatment effects of the basic info and the coordination message are equal.

Table 7: Heterogeneous impact by type of information treatment

	Log(vote)		Vote share	
	(1)	(2)	(3)	(4)
Basic info	0.026*	0.026*	0.002	0.002
	(0.014)	(0.014)	(0.005)	(0.005)
Basic info*Any crim	-0.035		0.001	
	(0.036)		(0.009)	
Info+Ethnic	0.020	0.020	0.001	0.001
	(0.020)	(0.020)	(0.005)	(0.005)
Info+Ethnic*Any crim	-0.012		-0.002	
	(0.045)		(0.009)	
Info+Coord	0.021	0.021	0.003	0.003
	(0.018)	(0.018)	(0.005)	(0.005)
Info+Coord*Any crim	-0.048		-0.007	
	(0.041)		(0.009)	

(continued)

Table 7: Heterogeneous impact by type of information treatment *(cont.)*

	Log(vote)		Vote share	
Basic Info*Non-murder crime		-0.014		0.002
		(0.035)		(0.009)
Basic Info*Murder-related charges		-0.099		-0.001
		(0.071)		(0.014)
Info+Ethnic*Non-murder crime		0.002		0.001
		(0.045)		(0.009)
Info+Ethnic*Murder-related charges		-0.057		-0.019
		(0.061)		(0.014)
Info+Coord*Non-murder crime		-0.025		-0.001
		(0.044)		(0.009)
Info+Coord*Murder-related charges		-0.116**		-0.028**
		(0.058)		(0.014)
Adjusted R^2	0.456	0.456	0.288	0.409
Observations	15522	15522	15534	15534

Standard errors in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Overall, the results in Section 4 suggest that voters do care about the quality of candidates being elected to office and will update their voting decisions accordingly. Still, information can help improve political selection into office along quality dimensions that voters care about when coupled with messaging that helps voters overcome the likely hurdles they may face in actualizing the information into action. Indeed, information may be critical to helping voters coordinate.

CONCLUSION

Improving political selection has the potential to have long-lasting impacts on economic development and social values. Yet, many democratic countries continue to struggle with electing high-quality candidates into office. India, the world's largest democracy, has a rich democratic history but also faces a growing problem of criminals in politics. In this study, we aim to understand what constraints Indian citizens face, if any, in electing non-criminal candidates to office and the extent to which lack of information is a salient barrier. We partner with three large telecom companies and send sizable proportions of the populations of a large set of randomly selected villages voice and text messages containing information about the criminal charges facing their major party candidates just days before the Uttar Pradesh state assembly elections of 2017.

Our results suggest that one reason for the pervasive election of criminals in this context does seem to be that voters face information constraints, as we observe a change in voting patterns once criminality information is provided. This does not seem to be driven simply by the fact that voters are being encouraged to think about who they vote for, as the content of the information determines the magnitude and direction of the response. Under the information treatments those facing murder charges experience a 12 percent decline in the number of votes they receive, leading to a three-percentage point decline in their vote share. This is a non-trivial magnitude when we consider the winning margins of the election we targeted with this campaign. Of the 403 races held across UP in 2017, roughly 20 percent were determined by a margin of three percentage points or less.

From a policy perspective, these results provide evidence that low-cost, easily-scalable, mobile-based information campaigns can be a powerful tool to empower citizens in developing countries, especially those living in rural areas with weaker access to election-related information through newspapers or internet, to make more informed decisions at the ballot box. In addition, the fact that voters responded most strongly to the most serious charges also helps alleviate concerns that spreading criminality information will lead to good candidates losing elections due to petty or spurious charges.

In future versions of this paper, we plan to add several layers of analysis to deepen our understanding of the mechanisms driving the patterns we observe. We plan to make use of market share data shared from our telco partners as well as pick-up and listening rates of our voice messages to calculate different measures of treatment intensity that can be used for heterogeneity analysis. In addition, we will examine potential spillover effects, conduct cost-effectiveness calculations, and examine potential impacts on the identity of who actually wins assembly elections. We will also be able to generate measures of the extent of ethnic voting, using detailed data on voter lists, and assess whether nudge-style interventions can reduce it.

REFERENCES

Aker, J., Collier, P., Vicente, P.C. (2015) Is Information Power? Using Cell Phones and Free Newspapers During an Election in Mozambique. *The Review of Economics and Statistics*.

Banerjee, A., Pande, R. (2009) Parochial Politics: Ethnic Preferences and Politician Corruption.

Banerjee, A., Green, D., Pande, R. (2012) Can Voters be Primed to Choose Better Legislators? Evidence from Voter Campaigns in India.

Banerjee, A., Kumar, S., Pande, R., Su, F. (2011) Do Informed Voters Make Better Choices? Experimental Evidence from Urban India.

Banerjee, A., Green, D., McManus, J., Pande, R. (2014) Are Poor Voters Indifferent to Whether Elected Leaders are Criminal or Corrupt? *Political Communication*.

Bratton, M. (2008) Vote Buying and Violence in Nigerian Election Campaigns. *Electoral Studies* 27(4): 621–632.

Chandra, K. (2007) *Why Ethnic Parties Succeed: Patronage and Ethnic Head Counts in India*. Cambridge University Press.

Chong, A., Ana, L., Karlan, D., Wantchekon, L. (2015) Does Corruption Information Inspire the Fight or Quash the Hope? A Field Experiment in Mexico on Voter Turnout, Choice, and Party Identification. *The Journal of Politics* 77(1): 55–71.

Dale, A., Strauss, A. (2009) Don't Forget to Vote: Text Message Reminders as a Mobilization Tool. *American Journal of Political Science* 53(4): 787–804.

Iyer, L., Mani, A. (2012) Traveling Agents: Political Change and Bureaucratic Turnover in India. *Review of Economics and Statistics* 94(3): 723–739.

Malhotra, N., Michelson, M., Rogers, T., Valenzuela, A.A. (2011) Text Messages as Mobilization Tools: The Conditional Effect of Habitual Voting and Election Salience. *American Politics Research* 39(4): 664–681.

Marx, B., Pons, V., Suri, T. (2015) The Perils of Building Democracy in Africa.

Myerson, R.B. (1993) Incentives to Cultivate Favored Minorities Under Alternative Electoral Systems. *American Political Science Review* 87(4): 856–869.

Myerson, R.B. (1999) Theoretical Comparisons of Electoral Systems. *European Economic Review* 43(4): 671–697.

Pande, R. (2011) Can Informed Voters Enforce Better Governance? Experiments in Low-Income Democracies.

Prakash, N., Rockmore, M., Uppal, Y., et al. (2015) Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India. *Households in Conflict Network (HiCN), The Institute of Development Studies, University of Sussex*.

Vaishnav, M. (2012) The Merits of Money and Muscle: Essays on Criminality, Elections and Democracy in India.

Vicente, P.C., Wantchekon, L. (2009) Clientelism and Vote Buying: Lessons from Field Experiments in African Elections. *Oxford Review of Economic Policy* 25(2): 292–305.