Coordinating Voters against Criminal Politicians: Evidence from a Mobile Experiment in India

Siddharth George, Sarika Gupta, Yusuf Neggers*

November 26, 2018

Abstract

Adverse selection to political office is now a salient concern in some mature democracies, but it is commonplace in the developing world. In India, 9 percent of legislators face charges for murder, kidnapping, rape, or armed robbery. Using a field experiment in the context of the 2017 Uttar Pradesh state assembly elections, we test the theory that criminal politicians are elected in part because voters lack information to screen for and coordinate on good candidates. We partnered with three major Indian telecom companies to conduct a mobile-based voter information experiment across more than 3,800 villages. Approximately 450,000 mobile subscribers in treatment villages received a voice and text message informing them about the criminal charges against candidates in their constituency. We find that voters respond to the content of the information provided – votes for candidates with severe charges drop by 7.7 percent and votes for candidates with no charges increase by 6.7 percent. In addition, overall turnout increases by 1.6 percent. Effects are strongest when the information is coupled with a coordination treatment, in which individuals are informed that many other voters are also receiving the message. The results suggest that voter frictions such as information asymmetry and coordination failure may cause bad political equilibria to persist.

*Siddharth Eapen George, siddharthgeorge@fas.harvard.edu, Harvard University; Sarika Gupta, sarikagupta@fas.harvard.edu, World Bank; Yusuf Neggers, yneggers@umich.edu, University of Michigan. We thank our research partner Manoj Kumar at the Center for Governance and Development in India for deep institutional knowledge about election campaigns in Uttar Pradesh, and for invaluable support in implementing the experiment. We are indebted to our advisor Rohini Pande for her extensive support and advice throughout this project. We would also like to thank Abhijit Banerjee, Robert Bates, Kirill Borusyak, Emily Breza, Melissa Dell, Ryan Enos, Michael Kremer, Horacio Larreguy, Filip Matejka, Eduardo Montero, Vincent Pons, Nishith Prakash, Pia Raffler, Gautam Rao, Deepak Saraswat, Andrei Shleifer, Shashank Sreedharan, Henrik Sigstad, and Edoardo Teso for useful feedback and helpful conversations. We thank seminar participants at Harvard and Brown for useful feedback and ideas. Financial support from the J-PAL Governance Initiative, the Harvard Lab for Economic Applications and Policy, and the Watson Institute for International and Public Affairs at Brown University is gratefully acknowledged.

1 Introduction

Adverse selection to political office has become a increasingly salient concern in mature democracies, but it is commonplace in the developing world. Understanding how to improve political selection may also be particularly important for development in low-income democracies, where elections give voters de jure power but formal institutions impose fewer constraints on the in-office behavior of politicians.

In this paper, we aim to understand why Indian voters continue to elect criminals in to public office and measure whether mobile-based information campaigns can improve political selection. Criminality is a serious concern in Indian politics—34% of the Members of Parliament (MPs) in 2014, for example, were facing criminal charges, including many for violent crimes such as murder, rape, kidnapping, and armed robbery. Moreover, recent work suggests that criminal MPs reduce economic growth and increase poverty and crime in their constituencies [Prakash et al., 2015]. We carry out a large-scale field experiment to measure the role of information and voter coordination in determining voting behavior and election outcomes in this setting.

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 3 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 3,800 villages text and voice messages 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 which group their village was randomly assigned to. In a first group of treatment villages, individuals are given the *basic information message*, which urges 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 their major party candidates. 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. Finally, individuals in a fourth group of treatment villages receive the *women's mobilization message*, which includes the same request that recipients get to know their candidates and think carefully before voting, plus an encouragement of female turnout.

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, gathered from Uttar Pradesh Chief Election Office.

We find, pooling across the three information treatments, that voters respond to the information content of the messages. Candidates facing no criminal charges receive a significant 2 percent increase in votes in areas receiving the information treatments, while candidates with murder charges see a 12 percent reduction in votes. As a result, candidates with murder charges see a 3 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 6.7 percent and those by candidates with murder-related charges (murder or attempted murder) are reduced by 7.7 percent. These results suggest that voters prefer clean candidates to criminal candidates, and vote against criminal candidates when informed about their type. The campaign also resulted in a 1.6 percent increase in overall turnout at polling stations receiving the infromation treatments as compared to control stations.

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 larger in magnitude and more significant in the information treatments that include the coordination message. In other words, voters who received information about criminality and also a public signal that others also received this message were more likely to punish candidates with serious criminal charges at the ballot box. This suggests that information on its own may not be sufficient to improve political selection in settings where voters also face barriers to coordination.

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 3 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.

2 Background

2.1 Indian Elections

India became the world's largest democracy on August 15, 1947. Unlike many developing countries have that transitioned in and out of democratic rule over the past century, India has maintained its democratic tradition with free and fair elections for the past 70 years. Yet this has not come without its challenges, as Indian politics is mired with ethnic fractionalization [Chandra, 2007], corruption [Bussell, 2012], and criminality [Prakash et al., 2015]. India also has over 200 political parties, with 7 parties officially recognized as National parties and the remaining categorized as state or regional parties. A unique feature of Indian politics is that all registered parties must have an associated symbol, and these symbols can be at times more widely recognized than the name of the party itself.

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, and empirical evidence shows that Indian MLAs facing criminal charges generate 22-percentage point lower economic activity than their non-criminal counterparts [Prakash et al., 2015].

2.2 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 low human development indicators 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. Nearly 22% of MLAs elected to office in 2012 faced serious criminal charges like murder, rape, kidnapping and extortion (Association for Democratic Reform, 2012). 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 an ideal 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.

2.3 Uttar Pradesh State Assembly Elections 2017

Given the sheer size of the electorate in UP, elections take place in phases. In 2017, there were 7 election phases, one every 4 days between February 11, 2017 – March 8, 2017. Each phase of the election covered 40-75 of the total 403 constituencies in UP[1]. There were four major parties vying for power in the elections: the Bharatiya Janata Party (BJP), the Bahujan Samaj Party (BSP), the Indian National Congress (Congress), and Samajwadi Party (SP). These parties are represented by the following party symbols: a lotus flower, an elephant, an open hand, and a cycle, respectively. This election was a landslide victory

[1]See Figure 2 for a constituency-level map of Uttar Pradesh.

for the BJP, who won 325 seats, representing over a three-fourths majority.

As recent trends from UP would have predicted, there were many candidates facing criminal charges standing for office during the 2017 elections. To give a sense of how common criminality is in this context, Table 1 provides a snapshot of the criminal charges facing the major party candidates standing for election in Phase 4 in the 38 constituencies targeted with our interventions. As seen in the table, of the 119 candidates captured in our dataset, 35% face at least one criminal charge, and over 40% of these individuals face charges for violent crimes.

Figures 1 shows the breakdown of criminality by political party, and we see that parties do vary to some extent in the nature of criminality facing their candidates. The BJP stands out as having both the highest percentage of criminals and the highest percentage of violent criminals. At the other extreme, while the Congress party has a moderate number of criminal candidates, non of them face violent criminal charges. To ensure that these differences across parties are not driving our results, we include specifications with party fixed-effects in each of our main regression tables.

What does voting for criminals look like in UP in the absence of our interventions? Table 2 shows the result of running fixed effects regressions of vote share on candidate criminality in the control villages in our sample. As seen in Column 1, criminal candidates on average receive a 6 percentage point higher vote share than non-criminal candidates, but this general result does not hold when we include party fixed effects in Column 2. In Columns 3 and 4, we compare candidates with non-violent criminal charges to those with violent criminal charges. Here, we see that even when accounting for party fixed effects, violent criminals are rewarded at the ballot box. Column 4 in Table 2 shows that violent criminals on average receive vote shares that are almost 5 percentage points higher than non-criminal candidates. Thus, at status quo, it does not appear that citizens are punishing criminals and may even reward them at the polls. With our study, we aim to understand the role of information, or lack thereof, regarding the criminal charges facing

candidates in explaining this relationship.

3 Research Design

3.1 Intervention Structure

3.1.1 Message Content and Execution

In order to carry out our intervention, we partnered with 3 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%. 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 in to effect 1 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:

1. Women's Mobilization Message: This message simply urges citizens to learn about their candidates and make well-formed decisions on election day, while encouraging

females to turn out to vote. The purpose of this intervention is two-fold. One, given the traditionally low turnout of female voters in UP even in comparison to other Indian states, we are interested in understanding if this kind of mass media campaign can facilitate higher turnout. In addition, it is possible that women have different preferences regarding politician characteristics than men, especially as it pertains to candidate criminality, so increasing female turnout may also indirectly decrease vote share of criminals. The script used for the voice message in this intervention is as follows:

"This message is from an unbiased, non-political NGO, Center for Governance and Development. Women across the country are voting in record numbers. When all household members vote, your family's power increases. So definitely encourage all women to vote! Get to know your candidates correctly, and on Election Day, give your vote only after thinking carefully!"

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 1 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.

By structuring the messages in this way, we allow citizens to not only learn about the magnitude of criminal charges facing a given candidate, but also differentiate between violent and non-violent charges, as presumably these may weigh differently in their voting decisions. Following the categorization standards of the legal code in India, the following crimes are included in the violent category in our messages: murder, attempt to murder, culpable homicide, attempt to commit culpable homicide, rape, attempt to commit rape, kidnapping and abduction, dacoity, preparation and assembly for committing dacoity, robbery, and arson. For all messages containing criminality information, the order of the candidates was randomized to avoid any biases in rank order affecting voter response and thus interpretation of the outcome.

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>>."

Due to different contractual agreements with different telecom companies, some of the above-mentioned interventions followed slightly different blast protocols than others. 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. Individuals who received women's mobilization message received one voice and one text message two days before the election, and the same voice message again the day before the election.

In total, the women's mobilization message was sent to Airtel customers across approximately 320 villages. Each of the three information interventions was sent to Vodaphone and Idea customers across about 430 villages. The next section provided details on the sampling and randomization.

3.1.2 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 2 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 1 and 2 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 treatments 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% coverage rate or lower). Together, these yield an experimental sample of 4,131 villages across 38 ACs.

We aimed to reach approximately 500,000 individuals with our messaging campaigns in Phase 4. 80 percent of this total was allocated equally across the 3 candidate-information arms (basic information, information plus ethnic-voting, and information plus coordination) and 20 percent to the women's mobilization arm, with the total number of treated individuals allocated across ACs in proportion to their populations. Villages were then randomly assigned across the 4 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.

To alleviate potential concerns regarding the validity of the randomization before proceeding with analysis of our experiment, we follow the standard approach of testing for

balance in a set of observable pre-election characteristics across our treatment and control villages. In particular, we consider in Table 3 the following village-level variables: total population, female population share, SC/ST population share, literacy rate, total number of registered voters, number of polling stations. We see that the average village in our sample has roughly 1,500 inhabitants. Roughly 48 percent of these individuals are female, 30 percent are SC/ST, and 56 percent are literate. In addition, there are roughly 1,200 total registered voters and 1.3 polling stations per village on average. Examining the coefficients from a regression of each village-level characteristic on a set of treatment dummies and the set of randomizations strata reveals no systematic significant differences. In particular, the equality of only 4 out of 30 comparisons can be rejected at the 10 percent level or below, approximately the rate that would be expected by chance.

3.2 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 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.

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.

3.3 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:

$$Y_{cpva} = \alpha_a + \beta Info_{va} + \theta Crim_{ca} + \phi \left(Info_{va} * Crim_{ca} \right) + \mathbf{X'_{pva}} \lambda + \epsilon_{cpva}. \tag{1}$$

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:

$$Y_{pva} = \alpha_a + \beta Info_{va} + \mathbf{X'_{pva}}\lambda + \epsilon_{pva}. \tag{2}$$

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 3 indicators correpsonding to the three different information treatment arms. Standard errors are clustered by census village.

4 Results

4.1 Impact of Information on Electoral Outcomes

A primary outcome of interest in this analysis is whether or not the information-based interventions changed the voting decisions of citizens. Table 4 shows how the polling-station-by-candidate-level votes received by candidates with different criminal backgrounds changed as a result of the information interventions, pooling across all three interventions that provided criminality information. Columns 1-3 show the change in vote shares for those without and those with any criminal charge, regardless of the nature of the charge. Across all three columns, we see that candidates who are shown in messages to have no criminal charges receive a significant roughly 2 percent increase in votes. Candidates with any criminal charges on average see no effects on their votes.

Voters however may respond differently based on the revealed pattern of charges. In columns 4-6 of Table 4, we examine how voters respond to different types of criminal charges facing their major party candidates. In this case, clear differential impacts of the treatments by severity of criminal charge are observed. There is a large and significant overall decrease in votes for murder-charged of 12 percent. Those with attempted-murder charges see a smaller, less-precisely estimated decline in votes, and those with non-murder-related charges see essentially no difference in votes. Figure 4 presents the results graphically, demonstrating a clear monotonic relationship between severity of charge and magnitude of negative voter response. 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. We repeat this exercise in Table 5, considering candidate vote shares rather than ln votes as an outcomes. A similar pattern emerges – candidates with the most severe charges see their vote share drop significantly by 3 percentage points, while the effect attenuates as the revealed charges become less severe.

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 serious criminal charges experiencing the largest penalty at the ballot box. 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.

Panel A considers the set of polling stations in constituencies where at least one candidate has a murder-related charge. Mirroring the candidate-by-station-level results, we observe that total votes across all candidates without any criminal charges increase by an average of 6.7 percent and votes for candidates with murder-related charges drop by 7.7 percent. These effects, together with a statistically insignificant increase in votes for candidates with only non-murder-related criminal charges, yield a combined increase in total turnout of 1.6 percent. Turning in Panel B to the set of polling stations where no candidates have a murder-related charge, we see that the positive impact on votes for "clean" candidates disappears. This difference across Panels A and B suggests that having the reference point of a competing candidate with a severe criminal charge is needed for the information treatment to increase votes for non-criminally-charged candidates.

Overall, the results presented in Tables 4-6 suggest that the criminality information provided 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

available [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.

4.2 Heterogeneity by type of message: the impact of coordination

Our interventions included three informational treatments. One provided only basic information on candidate criminality, while the others combined this basic information with other messaging aimed at either: providing an 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 the 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 information plus the coordination message increases vote shares for "clean" candidates by roughly 0.6 percentage points. These effects are statistically significant, though not large in magnitude. Moreover, treatment effects on clean candidates are significantly different between the coordination message — which increases vote share of the clean candidate — and the basic information message, which has no such impact.

We also examine the types of crimes that elicit a negative response from voters and

whether the ethnicity or coordination messages facilitate this response to a greater extent than the basic information message. For this analysis, we consider how voters across each informational intervention respond to candidates facing murder-related (attempted murder or murder) charges or only non-murder-related charges. All columns show an insignificant decline of roughly 0.8 percentage points in vote share for candidates with murder-related charges in polling stations that received the basic information treatment, and an insignificant decline of 1.5 percentage points for stations receiving the ethnic voting message. In contrast, the vote share for candidates facing a murder-related charge in polling stations that received the coordination message declines significantly by approximately 2.5 percentage points.

The results presented in Table 7 indicate that voters respond more strongly to criminality information when they additionally receive a public signal telling them that others have also received the information. 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, but information on its own may not be sufficient in contexts where voters feel pressure to follow the majority or have long-standing traditions of ethnic voting. Still, information can help improve political selection in to 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 in to action. Indeed, information may be critical to helping voters coordinate.

5 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 in to 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 3 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 3 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.

Bibliography

References

Jenny Aker, Paul Collier, and Pedro C Vicente. Is Information Power? Using cell phones and free newspapers during an election in Mozambique. *Review of Economics and Statistics*, 2015.

Abhijit Banerjee and Rohini Pande. Parochial politics: Ethnic preferences and politician corruption. 2009.

Abhijit Banerjee, Donald Green, and Rohini Pande. Can Voters be Primed to Choose Better Legislators? Evidence from Voter Campaigns in India. 2012.

Abhijit V Banerjee, Selvan Kumar, Rohini Pande, and Felix Su. Do Informed Voters Make Better Choices ? Experimental Evidence from Urban India. 2011.

Abhijit V. Banerjee, Donald Green, Jeffrey McManus, and Rohini Pande. Are Poor Voters indifferent to whether elected leaders are criminal or corrupt? *Political Communication*, 2014.

Michael Bratton. Vote buying and violence in nigerian election campaigns. *Electoral studies*, 27(4):621–632, 2008.

Jennifer Bussell. *Corruption and reform in India: Public services in the digital age*. Cambridge University Press, 2012.

Kanchan Chandra. *Why ethnic parties succeed: Patronage and ethnic head counts in India*. Cambridge University Press, 2007.

Alberto Chong, L Ana, Dean Karlan, and Leonard Wantchekon. 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, 2015.

Allison Dale and Aaron Strauss. Don't forget to vote: text message reminders as a mobi-

lization tool. *American Journal of Political Science*, 53(4):787–804, 2009.

Association for Democratic Reform. Analysis of criminal, financial, and other details of newly elected mlas of the uttar pradesh assembly elections 2012. *Press Release*, 2012.

Lakshmi Iyer and Anandi Mani. Traveling agents: political change and bureaucratic turnover in india. *Review of Economics and Statistics*, 94(3):723–739, 2012.

Neil Malhotra, Melissa R Michelson, Todd Rogers, and Ali Adam Valenzuela. Text messages as mobilization tools: The conditional effect of habitual voting and election salience. *American Politics Research*, 39(4):664–681, 2011.

Benjamin Marx, Vincent Pons, and Tavneet Suri. The Perils of Building Democracy in Africa. 2015.

Roger B Myerson. Incentives to cultivate favored minorities under alternative electoral systems. *American Political Science Review*, 87(04):856–869, 1993.

Roger B Myerson. Theoretical comparisons of electoral systems. *European Economic Review*, 43(4):671–697, 1999.

Rohini Pande. Can Informed Voters Enforce Better Governance? Experiments in Low-Income Democracies, 2011. ISSN 1941-1383.

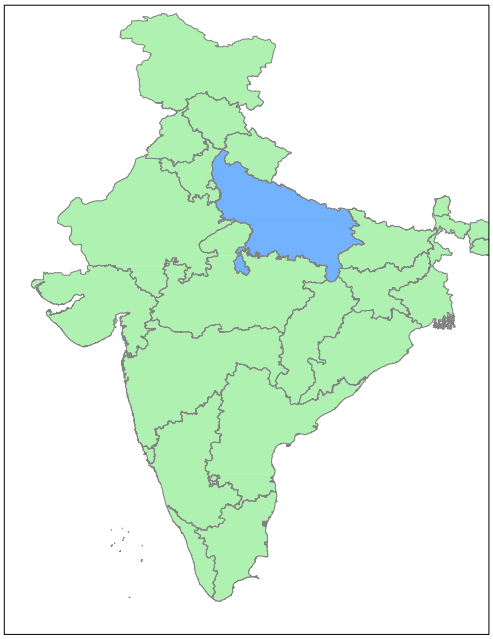
Nishith Prakash, Marc Rockmore, Yogesh Uppal, et al. Do criminally accused politicians affect economic outcomes? evidence from india. *Households in Conflict Network (HiCN), The Institute of Development Studies, University of Sussex*, 2015.

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

Pedro C Vicente and Leonard Wantchekon. Clientelism and vote buying: lessons from field experiments in African elections. *Oxford Review of Economic Policy*, 25(2):292–305, 2009.

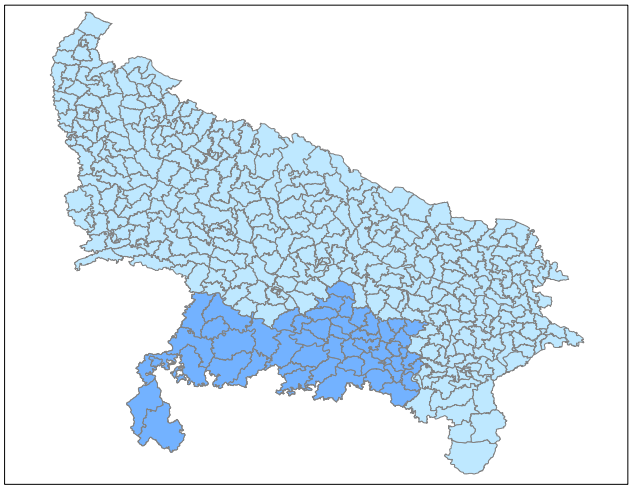
Figures and Tables

Figure 1a: Uttar Pradesh location in India



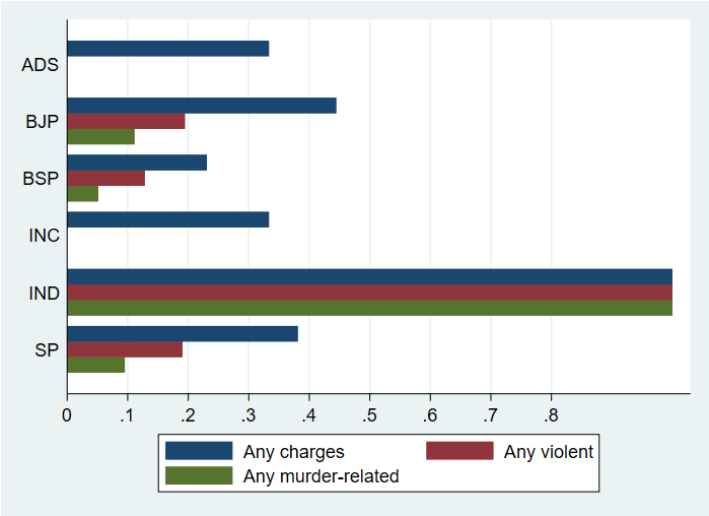
Notes: This figure shows the location of the state of Uttar Pradesh, the site of our experiment. We conducted our experiment around the State Assembly elections in Uttar Pradesh, which were held in March 2017.

Figure 1b: Experimental constituencies in Uttar Pradesh



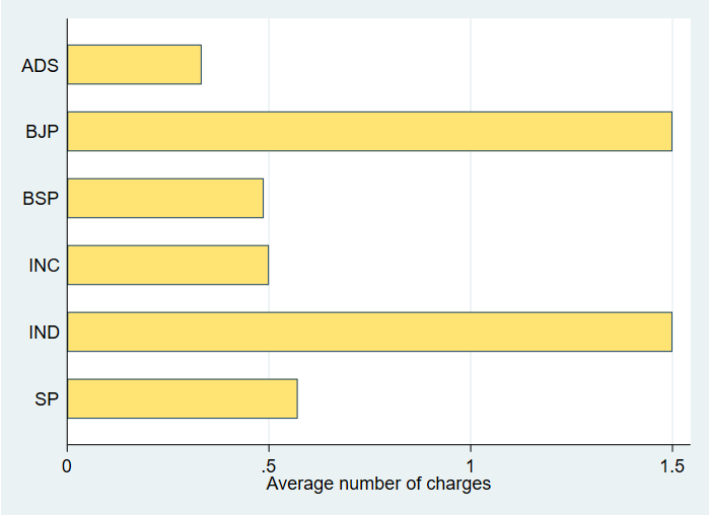
Notes: This figure shows the 49 assembly constituencies in Uttar Pradesh where we ran our mobile-based voter information campaign.

Figure 2a: Criminal charges by candidate party – type



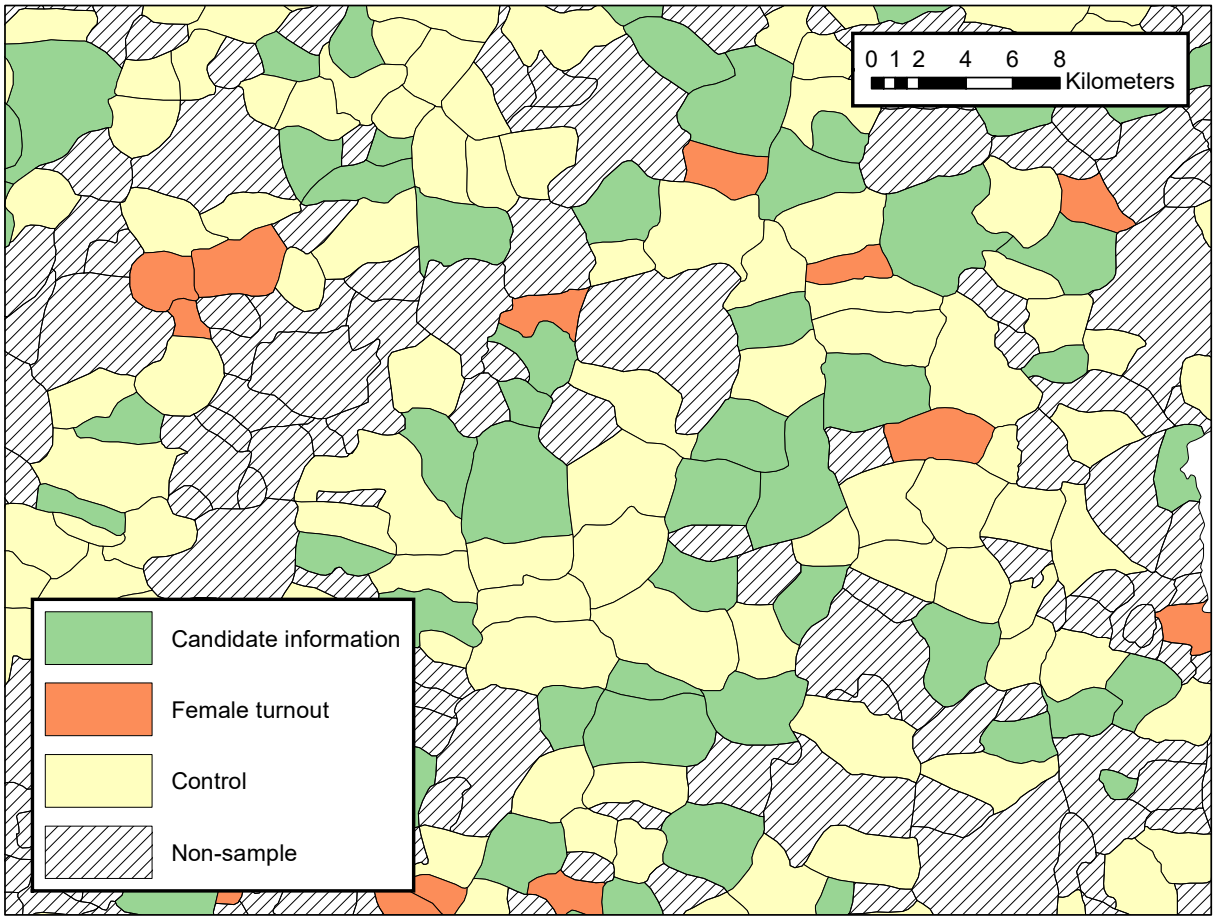
Notes: This figure presents the distribution of candidates with criminal charges by party and by type of charge. Violent crimes refer to murder, attempt to murder, rape, kidnapping, extortion and armed robbery.

Figure 2b: Criminal charges by candidate party – number



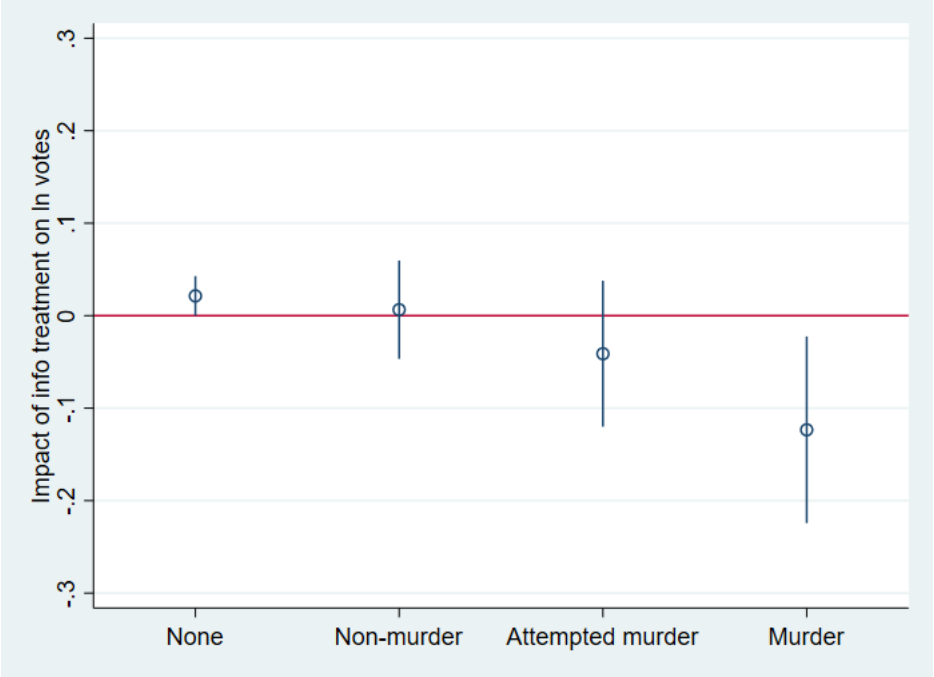
Notes: This figure presents summary statistics on the average number of charge per candidate by party for the major parties contesting in the 2017 UP state assembly elections. ADS refer to the Apne Dal (Sonelal), BJP refers to the Bharatiya Janata Party, BSP refers to the Bahujan Samaj Party, INC refers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

Figure 3: Example variation in randomized village treatment status



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

Figure 4: Relationship between information impact and charge-type revealed



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

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

	Mean (1)	SD (2)	Obs. (3)
A. Candidate level			
Criminal charge	0.352	0.480	119
Violent charge	0.151	0.360	119
Murder-related charge	0.084	0.078	119
B. Constituency level			
Any charge	0.795	0.409	39
Any violent charge	0.436	0.502	39
Any murder-related charge	0.256	0.196	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 consituencies with at least one candidate facing a criminal charge of each type.

Table 2: Criminal charges and electoral advantage

	Vote share			
	(1)	(2)	(3)	(4)
Criminal charges	0.064**	0.025		
	(0.028)	(0.018)		
Non-violent charges			0.027	0.007
			(0.032)	(0.021)
Violent charges			0.103**	0.048*
			(0.040)	(0.025)
Observations	8,645	8,645	8,645	8,645
Constituency FE	X	X	X	X
Party FE		X		X

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

Table 3: Balance check

	Control (1)	Basic Info (2)	Info + Coord (3)	Info + Ethnic (4)	Female Turnout (5)	Diff. (2) - (1) (6)	Diff. (3) - (1) (7)	Diff. (4) - (1) (8)	Diff. (5) - (1) (9)
Population	1541.5	1570.3	1560.5	1529.9	1442.4	29.0	23.3	-11.4	-60.9
	[914.2]	[975.0]	[921.2]	[934.7]	[892.3]	(49.2)	(47.9)	(48.6)	(53.0)
Share female	0.478	0.478	0.478	0.478	0.477	-0.000	-0.000	-0.000	0.002*
	[0.023]	[0.022]	[0.025]	[0.024]	[0.021]	(0.001)	(0.001)	(0.001)	(0.001)
Share literate	0.565	0.569	0.570	0.572	0.567	0.004	0.004	0.006	-0.003
	[0.087]	[0.081]	[0.083]	[0.083]	[0.087]	(0.004)	(0.004)	(0.004)	(0.004)
Registered voters	1219.4	1225.8	1181.4	1223.2	1185.2	5.8	-36.9	2.3	-10.2
	[561.0]	[572.0]	[542.2]	[533.5]	[567.1]	(29.5)	(28.9)	(28.3)	(33.5)
Polling stations	1.34	1.32	1.31	1.33	1.33	-0.02	-0.03	-0.01	-0.00
	[0.47]	[0.47]	[0.46]	[0.47]	[0.47]	(0.02)	(0.02)	(0.02)	(0.03)
Observations	2,206	430	421	422	318				

Notes: This table compares average characteristics of all of the villages in our sample across the control and treatment groups. Columns 1 – 5 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, and (6) female mobilization message group, respectively. Columns 6-9 report the coefficients from an OLS regression of the listed outcome on an the treatment indicators. Additionally included are constituency fixed effects. Robust standard errors are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 4: Impact of information treatments on candidate votes

	ln votes					
	(1)	(2)	(3)	(4)	(5)	(6)
Information	0.0190*	0.0188*	0.0214*	0.0183*	0.0183*	0.0214*
	(0.0104)	(0.00985)	(0.0129)	(0.0104)	(0.0101)	(0.0129)
Information	-0.0296	-0.0305	-0.0352			
* Any criminal charge	(0.0350)	(0.0319)	(0.0319)			
Information				-0.0104	-0.00866	-0.0149
* Non-murder-related charge				(0.0380)	(0.0351)	(0.0351)
Information				-0.0527	-0.0566	-0.0625
* Attempted murder charge				(0.0645)	(0.0558)	(0.0521)
Information				-0.117*	-0.138**	-0.145**
* Murder charge				(0.0636)	(0.0676)	(0.0636)
Observations	13,410	13,410	13,410	13,410	13,410	13,410
Constituency FE	X	X		X	X	
Party FE		X			X	
Candidate FE			X			X

Notes: This table shows results from polling-station-by-candidate-level regressions of ln votes on criminal charges interacted with treatment. Information is a dummy for receiving any of the 3 information treatments. 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-Murder-related is a dummy variable that takes a value of 1 if the candidate faces charges that are all non-murder-related, Attempted murder is a dummy variable that takes a value of 1 if the candidate faces an attempted murder charge but no murder charges. Murder is a dummy if the candidate faces any murder charges. All regressions include controls for log total population, share female, share literate, log number of registered voters, and constituency fixed-effects. Columns 2 and 4 also include party fixed effects. Columns 3 and 6 include candidate fixed effects. Standard errors are two-way clustered at the village and candidate levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Impact of information treatments on candidate vote shares

	Vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Information	0.122	0.132	0.166	0.106	0.119	0.167
	(0.169)	(0.116)	(0.141)	(0.157)	(0.122)	(0.165)
Information	-0.566	-0.599	-0.680			
* Any criminal charge	(0.750)	(0.709)	(0.747)			
Information				-0.0354	-0.0165	-0.137
* Non-murder-related charge				(0.818)	(0.763)	(0.777)
Information				-1.447	-1.569	-1.526
* Attempted murder charge				(2.001)	(1.807)	(1.800)
Information				-2.751***	-3.119***	-3.434***
* Murder charge				(0.967)	(0.983)	(0.918)
Observations	13,580	13,580	13,580	13,580	13,580	13,580
Constituency FE	X	X		X	X	
Party FE		X			X	
Candidate FE			X			X

Notes: This table shows results from polling-station-by-candidate-level regressions of vote shares on criminal charges interacted with treatment. Information is a dummy for receiving any of the 3 information treatments. 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-Murder-related is a dummy variable that takes a value of 1 if the candidate faces charges that are all non-murder-related, Attempted murder is a dummy variable that takes a value of 1 if the candidate faces an attempted murder charge but no murder charges. Murder is a dummy if the candidate faces any murder charges. All regressions include controls for log total population, share female, share literate, log number of registered voters, and constituency fixed-effects. Columns 2 and 4 also include party fixed effects. Columns 3 and 6 include candidate fixed effects. Standard errors are two-way clustered at the village and candidate levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Polling station-level impacts of information treatments

	Candidates without charges		Candidates with murder-related charges		Candidates with other charges		Overall turnout
	ln votes	Vote share	ln votes	Vote share	ln votes	Vote share	ln votes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Any candidate with murder-related charges							
Information	0.067*	1.414	-0.077*	-2.230**	0.055	-0.387	0.016*
	(0.039)	(1.140)	(0.047)	(1.032)	(0.087)	(1.818)	(0.009)
Observations	1,132	1,145	1,132	1,145	398	405	1,132
Control outcome mean	5.295	47.557	4.960	33.044	4.793	30.969	6.269
B. No candidate with murder-related charges							
Information	0.006	-0.118			-0.007	-0.034	0.008
	(0.018)	(0.569)			(0.027)	(0.698)	(0.007)
Observations	3,219	3,248			2,191	2,205	3,361
Control outcome mean	5.440	58.243			5.235	45.902	6.230

Notes: This table shows results from polling-station-level regressions of voting outcomes on information. Panel A is restricted to polling stations where at least 1 candidate faced any murder-related charges. Panel B is restricted to polling stations where no candidates faced any murder-related charges. Information is a dummy for receiving any of the 3 information treatments. All regressions include controls for log total population, share female, share literate, log number of registered voters, and constituency fixed-effects. Standard errors are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Polling station-level impacts by type of info treatment

	Vote share		
	(1)	(2)	(3)
Basic Info	-0.226	-0.041	-0.028
	(0.276)	(0.186)	(0.297)
Info + Ethnic	0.257	0.167	0.216
	(0.358)	(0.274)	(0.312)
Info + Coordination	0.722**	0.519**	0.521
	(0.281)	(0.239)	(0.376)
Basic Info x Non-murder-related	1.212	0.625	0.639
	(1.043)	(0.911)	(0.957)
Info+Ethnic x Non-murder-related	0.004	0.125	0.090
	(0.988)	(0.899)	(0.923)
Info+Coord x Non-murder-related	-1.405	-0.891	-0.936
	(1.234)	(1.193)	(1.195)
Info Basic x Murder-related	-0.464	-0.763	-0.938
	(1.821)	(1.761)	(1.752)
Info+Ethnic x Murder-related	-2.335	-1.716	-1.984
	(1.605)	(1.329)	(1.379)
Info+Coord x Murder-related	-3.974**	-3.196*	-3.094*
	(1.877)	(1.721)	(1.714)
Constituency FE	Yes	Yes	No
Party FE	No	Yes	No
Candidate FE	No	No	Yes
Observations	14,087	14,087	14,087

Notes: This table shows results from polling-station-by-candidate-level regressions of vote share on the individual information treatments interacted with different types of criminal charges. All data represented in this table comes from Phase 4 of the UP State Assembly Elections of 2017. In rows 1-5, the independent variables Basic Info, Info+Coord, Info+Ethnic are dummy variables that take a value of 1 if the candidate is standing in a polling station that received the basic information, information plus coordination, or information plus ethnic. In Rows 7-11, these treatment dummies are interacted with another dummy variable, Non-murder-related, which takes the value of 1 if the candidate faces any non-murder-related criminal charges. In Rows 13-17, the three treatment dummies are interacted with Murder-related, a dummy variable that takes the value of 1 if the candidate faces at least one murder-related charge. Regressions include controls for total population, share female, share SC/ST, share literate, number of registered voters, and constituency fixed-effects, party fixed-effects, or candidate fixed-effects, as indicated by "Yes" or "No" in the bottom panel. Standard errors, clustered at the village and candidate level, are shown in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$