# Technology and Protest: Online Appendix

Zuheir Desai* Alexander Lee†

October 3, 2019

The online Appendix is organized as follows. We first present additional hypotheses regarding confused voting, turnout and electoral fraud in Section A.1. Section A.2 and Section A.3 discuss whether EVMs had an effect on the number of valid votes and whether EVMs increased fragmentation in a constituency. We then address whether electronic voting machines increased confused voting in Section A.4, and the question on turnout in Section A.5. We also address the impact of EVMs on fraud in Section A.6. Finally, we report tables including results about control variables from the main text in Section A.7.1, and all other tables are reported in Section A.7.2.

## A.1 Subsidiary Effects of Electronic Voting: Confused Voting, Turnout and Fraud

### A.1.1 Confused "Valid" Voting

We have already noted that EVMs usually reduce the number of invalid votes, and that this has usually been interpreted as a decline in *unintentional* errors. However, any reduction in unintentional invalid voting associated with voting machines may be apparent rather than real. Note that a voter with high cognitive costs ($C_C$) might, instead of casting an invalid ballot, "validly"

*Department of Political Science, University of Rochester, Harkness Hall, Rochester, NY 14627. Email: zuheir.desai@rochester.edu.

†Department of Political Science, University of Rochester, Harkness Hall, Rochester, NY 14627. Email: alexander.mark.lee@rochester.edu.

vote for the wrong candidate. Voters, confused by technology, might press buttons randomly or unskillfully, and these inputs are interpreted by the "forced choice" framework of the machines as votes for candidates other than their preferred one.

How would a confused voter deal with an EVM? If they merely press buttons at random, the introduction of voting machines would lead to a corresponding increase in "random" voting. This may lead to votes being distributed to candidates evenly across the board, thereby increasing vote fragmentation within the constituency. Alternatively, buttons in certain positions may be more likely to be chosen by confused voters. For example, Dee (2007) finds that the users of punch cards were more likely to vote for bookend candidates compared with users of other technologies. Such patterns would accord with the large literature that shows that voters often cast ballots using arbitrary heuristics, such as the ballot position of the candidate (Ho and Imai, 2008; Alvarez et al., 2004). The introduction of electronic voting machines could thus be associated with increases in vote for candidates in "favored" ballot positions—at the top of the machine, or around the eventual winner.

### A.1.2 Turnout

The preceding discussion assumed that former protest voters would still go to the polls and make a choice after the introduction of EVMs. It is certainly possible that voters unable to cast protest ballots would choose not to turn out at all. This is especially pertinent in cases like India, where voting is not mandatory. Note that given that their protest vote in the form of an invalid ballot did not affect the outcome of the result in the first place, however, it is not likely that this would be the case. Furthermore, if the expressive benefit from voting for minor parties ($E_M$) are relatively similar to that from invalid votes ($E$), then the introduction of EVMs should not have a major effect on turnout.

### A.1.3 Electoral Manipulation

A large literature in computer science has found a large number of security issues that render voting machines susceptible to fraud. Kumar and Walia (2011) provide a thorough comparative overview of technological and security features of voting machines around the world. Wolchok et al. (2010) specifically look at Indian machines and point out the many security shortcomings, leaving it vulnerable to electoral manipulation. To counter the possibility of mass electoral fraud, security experts have often recommended the introduction of some sort of paper record of vote, to allow the totals reported by the machines to be crosschecked. Theoretically, we should expect the introduction of this feature to enhance any security advantage, and any disadvantage to be lessened.

Proponents of voting machines, by contrast, have declared that EVMs are less susceptible to fraud than other forms of election technology. In particular, the complexity of the machines, or their built-in security features, may make it more difficult to suddenly insert votes in large numbers (ballot box stuffing), which is easy with paper ballots. Indian voting machines, for instance, do not allow the casting of more than five votes a minute. Since the probability of law enforcement intervention increases over time, this feature makes brief “booth captures” more difficult. If this is correct, the introduction of voting machines should be associated with reductions in turnout, not because voters are not turning out, but because the number of fraudulently cast ballots has been reduced. Unlike the general decline in turnout discussed in the last section, this should be concentrated in regions that were relatively more corrupt (since the number of fraudulently cast ballots to be eliminated is larger). This would further imply that the introduction of voting machines should reduce the vote share of candidates who were best positioned to commit fraud, such as candidates from the party which controls the state government.

## A.2 Effects on Valid Voting

The claim that the fall in invalid voting is normatively important hinges on the assumption that the voters who previously cast invalid votes now cast valid votes. If voters who previously cast invalid votes simply stopped turning out after the introduction of EVMs, the reform would have no political effect, and only a very doubtful normative value. This concern is especially valid because it appears that turnout may decrease with the introduction of EVMs (see Section A.5).

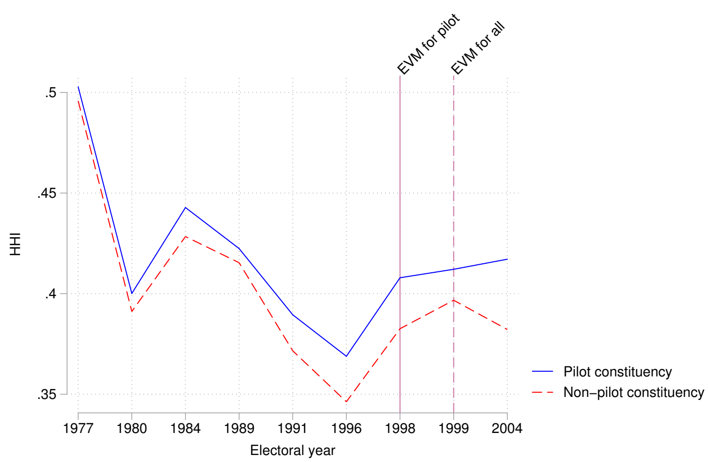
However, the results seem to suggest that EVMs had a net positive effect in terms of "enfranchisement," with the decline in invalid votes swamping the poorly estimated decline in turnout. These results are presented in Table A.7, which shows the results of a difference-in-differences model with the number of valid votes cast in a constituency as a dependent variable. The coefficient on EVMs is positive in all models, although it is not always significant. Thus, we can reasonably conclude that EVMs have an overall non-negative effect on enfranchisement of Indian citizens since they resulted in a smaller number of votes being disregarded as invalid.

Note that this estimated effect may represent an underestimate of the enfranchising effects of EVMs. To the extent that EVMs successfully prevent ballot box stuffing (their primary intended purpose), they should lead to a reduction in the number of legally valid but fraudulent votes, which would lead to EVM introduction having a spurious "disenfranchising" effect. The fact that the number of valid votes increases regardless is strong evidence that EVM introduction led many voters who would previously have cast invalid votes to cast valid ones.

## A.3 Fragmentation

The Herfindahl-Hirschman Index (HHI) is the sum of the squared vote shares of all candidates in a constituency. It is an indicator of the relative fractionalization in the electoral district. Thus, in the case of a small number of parties dominating the election, the HHI is close to 1, and if there are many parties with similar vote shares, then it is close to 0. As before, we first present evidence on the pre-trends of HHI in Figure A.1. The trends seem to move together, with the relatively urban and richer pilot constituencies showing more concentration of vote shares and the non-pilot, rural constituencies being more competitive (in terms of the fragmentation of the vote). The trends are relatively parallel for pilot and non-pilot constituencies, and the effect of lags and leads of the treatment is statistically insignificant (Table A.14).

Figure A.1: Pre-trends for HHI




*Notes.* The blue solid line plots the average HHI in all pilot constituency across election years while the red dashed line plots the average HHI in non-pilot constituencies. The year 1998 marks the last election before the introduction of EVMs. Thus, 1999 is the first post-treatment year for the pilot constituencies. In the year 2004, the non-pilot constituencies also used EVMs.

Table A.12 shows the effect of electronic voting machines (EVMs) on the HHI. EVMs have a negative effect on HHI in all models considered. The smaller the HHI, the more the fragmentation within the electoral district (as votes are divided among more candidates). Thus, a negative coefficient indicates that EVMs increase fractionalization. However, the coefficient in Column (2), the standard difference-in-differences model, is not significant. This is because HHI is affected by other time varying variables such as the number of candidates in the district. After having controlled for these variables, Columns (3) and (4) indicate that EVMs had a significant negative effect on the HHI. This effect is robust to phase-year controls.

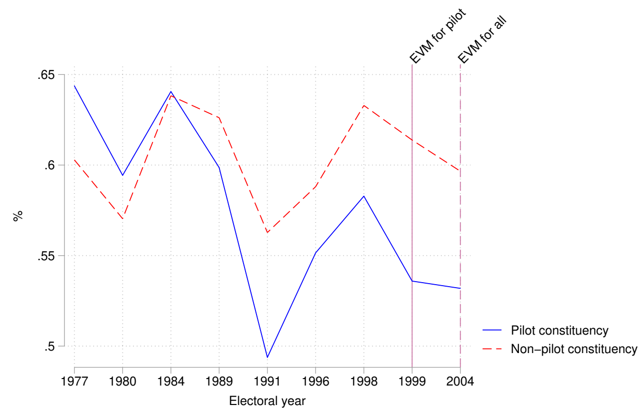
## A.4 Confused voting

Do voting machines lead to increases in valid votes cast in error, even as the number of invalid votes decreases? In the paper we showed that voters do not press buttons randomly. However, there is additional evidence that EVMs had little effect on confusion. We rely on the intuition that confused voters would be more likely to press buttons in certain positions than in others, even if they are unfamiliar with the candidate at that position. One possibility is that voting machines would increase "donkey voting": Choosing the candidate first on the machine. A large literature has shown that voting based on ballot order is a common heuristic among voters (Krosnick, Miller and Tichy, 2003; Ho and Imai, 2008), and we have some anecdotal evidence that voters in India use EVMs in this way (Banerjee, 2015). Ballot order in India is not random, with the candidates of nationally recognized parties being listed first (in alphabetical order in the state's official language) followed by the candidates of state recognized parties, and then all other candidates. Using this structure, we were able to reconstruct the ballot order for all the Hindi-speaking states during our time period. Table A.16 shows the relationship between EVMs and voting for the first placed candidate. There is little or no relationship between EVMs and the vote share of the candidate placed first on the ballot in all models. Another common voting error is to cast votes for candidates immediately above or below their actual preferred choice (Alvarez et al., 2004). Table A.18 and Table A.17 examine whether such "proximity effects" are exacerbated by EVMs. There is no evidence that candidates immediately above or below the winner on the ballot benefit from the introduction of voting machines.

## A.5 Turnout

Do voters who previously cast invalid ballots still turn out? In the Indian case, since EVMs make it impossible to cast an invalid ballot, voters who intentionally casted spoiled ballots could now loose their incentive to go to the polls. As before, we examine the pre-trends of the early treatment pilot constituencies and the non-pilot constituencies. Compared to the pre-trends of invalid vote rates, the pre-trends for turnout do not show evidence of parallel trends.

Figure A.2: Pre-trends for turnout




*Note:* The blue solid line plots the average turnout rate in all pilot constituency across election years while the red dashed line plots the average turnout vote rate in non-pilot constituencies. The year 1998 marks the last election before the introduction of EVMs. Thus, 1999 is the first post-treatment year for the pilot constituencies. In the year 2004, the non-pilot constituencies also used EVMs.

In particular, figure A.2 shows that there was a perceptible negative trend in turnout in the treatment districts relative to the control districts in the early 1990s,[1] though the gap did not appear to be increasing in the two elections before 1999. This trend may reflect the growing turnout gap in India between poor and rich voters, with rich voters tending to be less involved (Ahuja and Chhibber, 2012). The second column in Table A.22 conducts a placebo analysis by comparing the effects of the EVM treatment on turnout in the year 1999 versus other electoral years. According to the results, while the pilot constituencies have consistently smaller turnout rates compared to the non-pilot constituencies across all electoral years, the difference in the treatment year is larger than any other year.

Table A.13 examines the effect of EVM introduction on voter turnout. The results suggest

[1]The perceptible drop in turnout in pilot constituencies in 1991 could be because of the assassination of Rajiv Gandhi midway through the elections.

that EVMs have a slight negative effect on turnout. Substantively, the effect is a little over two percentage points, a little smaller than the overall observed decline in turnout during this period, from 62.5% in 1998 to 59% in 2004.

However, we are cautious about whether EVMs affect turnout. Firstly, the pre-trends seem to suggest that the parallel trends assumption is not valid in the case of turnout. Secondly, an analysis of lags and leads of treatment in Table A.22 shows that the pilot constituencies consistently were different from non-pilot constituencies in terms of turnout. Third, these results are not robust to clustering standard errors at the state level, or the state-year level. Thus, it seems likely that turnout rates within each state-year dyad are not independent. And, finally, Panel (c) of Table A.14 in particular shows that voting machines have no effect on turnout when the analysis is restricted to the geographically proximate constituency subsample and the matched constituency subsample.

## A.6 EVMs and Fraud

Wolchok et al. (2010) suggest that Indian voting machines, like elsewhere in the world, suffer from security issues, and that a technically sophisticated group with access to the machines could modify the hardware to produce desired results. These theoretical concerns parallel widespread rumors about attempts by the parties to modify the machines (Wolchok et al., 2010), and occasional reports of technical problems. Wolchok et al. (2010) are also critical of the ECI's procedures surrounding the storage of the machines, and skeptical that certain ECI security procedures (the random assignment of machines to booths, and the conduct of mock elections with machines before polling) address these concerns. It should be noted, however, that even if EVMs are vulnerable to fraud, this does not mean that they are more vulnerable than alternative technologies. After all, a fraudster with access to stored boxes of paper ballots could produce a fraudulent result with considerably less effort and technical knowledge than is necessary to manipulate stored machines.

### A.6.1 Partisan Effects

If EVMs were in fact altering the chances of successful electoral fraud, we should expect their introduction to increase the vote for specific parties or types of parties, especially those likely to be able to fraudulently manipulate the machines. Note that while study of whether different voting technologies favor or disfavor particular political parties has been the topic of discussion in the literature, there is little proof of systematic effects (as opposed to analyses of particular races) (Stewart, 2011).

We do not find any systematic effects on the vote shares of specific political parties, such as the INC or the BJP, or on the vote shares of electoral alliances such as the BJP-led National Democratic Alliance (NDA), the INC-led United Progressive Alliance (UPA),[2] or the Third Front. These results are not reported for reasons of space, but are available on request from the authors.

Table A.19 analyzes the effect of EVMs on the vote share of the incumbent party of the state government. In the Indian context, the state government is the agency with effective control over the police and the district administration, which they might use for electoral advantage. Despite the ECI's careful attempts to limit such influence, the state incumbents clearly have a much greater opportunity to engage in fraud than any other party, and a decline of the vote for this party in areas with EVMs would be strong evidence for fraud. Conversely, if EVMs had a positive effect on state incumbent vote share, we might suspect the sort of systematic machine tampering feared by Kumar and Walia (2011).

However, Table A.19 shows that there is little evidence for such an effect. EVMs have a small positive relationship with state incumbent vote share, but this effect is statistically insignificant at conventional levels. State incumbents thus appear not to be affected by the introduction of

[2]While the UPA was formally created after the 2004 election, the INC was allied with several regional parties during the 1998 and 1999 elections. We also examined whether EVMs had any effect on the vote shares of the INC+allies, and found no systematic effects.

EVMs, either because of the quality of the ECI's precautions or because EVMs in ineffective in preventing the types of fraud they use.

### A.6.2 Voter Verification

One of the defining features of "direct recording" EVMs is that votes are recorded on the memory unit of the machine, rather than on paper. This makes it impossible for voters to directly verify that their vote has been cast in the way that they wish, and theoretically possible to alter vote totals within the machine in ways that would be difficult to detect. The most commonly recommended solution to this problem is a voter-verified paper audit trail (VVPAT) (Kohno et al., 2004). VVPAT machines differ from other EVMs in that the voter receives a paper "receipt" for her vote, which can then be compared to the machine-reported totals in a post-election audit.

In 2013, the Indian supreme court ordered the election commission to introduce VVPAT technology in all elections. In the 2014 national election, eight constituencies had VVPAT. This makes possible a difference-in-differences analysis similar to that in Section A.6.1, using two years (2009 and 2014). Since the announced goal of VVPAT is the reduction in fraud, we will focus on the results for two outcomes that might plausibly be correlated with fraud: The level of voting for the state incumbent party and the turnout rate.[3]

Tables A.20 and A.21 show the results of this analysis. Relative to ordinary machines, the introduction of VVPAT machines appears to have no negative effect on turnout or vote for incumbents: If anything, turnout appears to increase very slightly in treated constituencies. The fact that the effect of VVPAT machines is indistinguishable from that of non-auditable eletronic voting machines does not mean that these innovations are useless, since this technology may possibly prevent election fraud in the future. It does, however, indicate that these machines are not associated with changes in political outcomes relative to 2004 and 2009, either because no large-scale fraud occurred during this period or because VVPAT has not decreased the types of fraud that did

[3] Results showing VVPAT has no association with invalid voting are not reported for reasons of space.

take place.

### A.6.3 Turnout and Fraud

It is possible that the effect of EVMs can be found not in the vote totals but in the turnout figures. We especially focus on regional variation in the turnout effect, given that we expect to see decreases in turnout in constituencies that are more prone to booth-capturing. If booth capturing was common before 1999, some portion of the turnout recorded by the ECI represents fraudulent votes, entered into the voter register and ballot box by armed goons. If the introduction of EVMs reduced the incidence of booth capture (as it was designed to do), we should expect turnout to decline with their introduction in areas where this practice was common.

Interestingly, the effect of EVMs on turnout is not larger in areas that would intuitively be identified as more corrupt. One commonly used measure of corruption in Indian public life is the tendency of many candidates to face serious criminal charges (Vaishnav, 2017; Aidt, Golden and Tiwari, 2011). Using Aidt, Golden and Tiwari's (2011) data on the criminal status of candidates in the 2004 and 2009 elections, we define a constituency as "criminal" if there was at least one criminal who ran for election. Table A.15 results show that there is no estimated effect of EVMs on turnout in these constituencies. Similar results (not reported for reasons of space) could be obtained by interacting EVM introduction with state-level poverty, insurgency, or location in the Hindi belt.

These weak results are consistent with design of the machines, since EVMs do not make it impossible for political parties to capture polling booths, but only increase the time it takes to do so. While it is still possible to take control of polling booths, the delay built into the machines means control must be maintained for a longer time if all the booth's ballots are to be casted. Anecdotal evidence suggests that political parties still indulge in fraudulent voting, even with the presence of EVMs (Rohde, 2004).

## A.7 Additional Tables

### A.7.1 Tables including results on control variables from the main text

Table A.1: Effects of EVMs on invalid vote rates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | -0.0196*** | -0.0173*** | -0.0174*** | -0.0185*** | -0.0169*** |
| | (0.000463) | (0.00113) | (0.00124) | (0.00154) | (0.00300) |
| INC vote share | | | -0.00226 | -0.00396 | |
| | | | (0.00318) | (0.00324) | |
| BJP vote share | | | -0.0114** | -0.0113** | |
| | | | (0.00376) | (0.00365) | |
| Victory margin | | | 0.0131* | 0.00806 | |
| | | | (0.00518) | (0.00497) | |
| # of candidates | | | -0.000347** | -0.000434*** | |
| | | | (0.000112) | (0.000115) | |
| Turnout | | | 0.0389*** | 0.0355** | |
| | | | (0.0110) | (0.0119) | |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Year FE | | Yes | Yes | | Yes |
| Phase-year FE | | | | Yes | |
| Constant | 0.0201*** | 0.0243*** | -0.00141 | 0.00552 | 0.0255*** |
| | (0.000461) | (0.000393) | (0.00783) | (0.00852) | (0.00115) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.456 | 0.700 | 0.722 | 0.762 | 0.676 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on invalid vote rates in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, and turnout rate, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.2: Effects of EVMs on Minor party vote shares

(a) **Diff-in-diff + controls**

| | (1) < 2.5% | (2) < 5% | (3) < 7.5% | (4) < 10% |
|---|---|---|---|---|
| EVM | 0.0198*** | 0.0316*** | 0.0387*** | 0.0289*** |
| | (0.00318) | (0.00379) | (0.00506) | (0.00685) |
| INC vote share | -0.0114* | -0.0272*** | -0.0220* | -0.0232+ |
| | (0.00484) | (0.00747) | (0.00990) | (0.0121) |
| BJP vote share | -0.00473 | -0.0121 | -0.0151 | -0.0289 |
| | (0.00610) | (0.0109) | (0.0148) | (0.0202) |
| Victory margin | 0.00344 | -0.0164 | -0.0384* | -0.0324 |
| | (0.00665) | (0.0115) | (0.0149) | (0.0200) |
| # of candidates | 0.00267*** | 0.00290*** | 0.00294*** | 0.00327*** |
| | (0.000315) | (0.000405) | (0.000548) | (0.000653) |
| Turnout | -0.0113 | -0.0407* | -0.0348 | -0.0657* |
| | (0.0106) | (0.0164) | (0.0233) | (0.0297) |
| Constituency FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Constant | 0.00705 | 0.0685*** | 0.0649*** | 0.0869*** |
| | (0.00819) | (0.0127) | (0.0180) | (0.0227) |
| $N$ | 1628 | 1628 | 1628 | 1628 |
| $R^2$ | 0.713 | 0.666 | 0.608 | 0.581 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(b) **Phase-year fixed effects**

| | (1) < 2.5% | (2) < 5% | (3) < 7.5% | (4) < 10% |
|---|---|---|---|---|
| EVM | 0.0203*** | 0.0319*** | 0.0380*** | 0.0281*** |
| | (0.00316) | (0.00403) | (0.00538) | (0.00718) |
| INC vote share | -0.0127* | -0.0259** | -0.0200+ | -0.0219+ |
| | (0.00500) | (0.00784) | (0.0104) | (0.0126) |
| BJP vote share | -0.00424 | -0.00957 | -0.0158 | -0.0183 |
| | (0.00658) | (0.0113) | (0.0156) | (0.0200) |
| Victory margin | 0.00296 | -0.0127 | -0.0370* | -0.0359+ |
| | (0.00669) | (0.0118) | (0.0156) | (0.0213) |
| # of candidates | 0.00271*** | 0.00307*** | 0.00298*** | 0.00320*** |
| | (0.000307) | (0.000424) | (0.000565) | (0.000673) |
| Turnout | -0.0205+ | -0.0432* | -0.0441+ | -0.0696* |
| | (0.0111) | (0.0181) | (0.0237) | (0.0328) |
| Constituency FE | Yes | Yes | Yes | Yes |
| Phase-year FE | Yes | Yes | Yes | Yes |
| Constant | 0.0170+ | 0.0697*** | 0.0741*** | 0.0903*** |
| | (0.00889) | (0.0145) | (0.0192) | (0.0266) |
| $N$ | 1601 | 1601 | 1601 | 1601 |
| $R^2$ | 0.726 | 0.680 | 0.622 | 0.588 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* Panel (a) conducts a basic diff-in-diff regression for all 5 measurements of minor candidate vote share on EVM, and includes controls, Panel (b) replaces electoral year fixed effects with phase-year fixed effects. All standard errors have been clustered at the constituency level.

Table A.3: Differentiated effects of EVMs for the BSP in and out of strongholds

(a) **BSP in Uttar Pradesh**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| EVM | 0.0153 | -0.0281 | -0.0114 | -0.00412 |
| | (0.0118) | (0.0190) | (0.0308) | (0.0310) |
| INC voteshare | | | -0.208** | -0.229** |
| | | | (0.0663) | (0.0723) |
| BJP voteshare | | | -0.137* | -0.0640 |
| | | | (0.0628) | (0.0817) |
| Victory Margin | | | -0.0511 | -0.108* |
| | | | (0.0562) | (0.0478) |
| # of candidates | | | -0.00105 | -0.00119 |
| | | | (0.00117) | (0.00101) |
| Turnout | | | -0.140 | 0.105 |
| | | | (0.143) | (0.152) |
| Constituency FE | | Yes | Yes | Yes |
| Year FE | | Yes | Yes | |
| Phase-year FE | | | | Yes |
| Constant | 0.216*** | 0.234*** | 0.377*** | 0.227* |
| | (0.00633) | (0.00742) | (0.0807) | (0.0913) |
| *N* | 255 | 255 | 255 | 236 |
| $R^2$ | 0.007 | 0.804 | 0.832 | 0.882 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(b) **BSP outside Uttar Pradesh**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| EVM | 0.00769*** | 0.00730* | 0.00748* | 0.00796* |
| | (0.00226) | (0.00306) | (0.00339) | (0.00377) |
| INC voteshare | | | -0.0453** | -0.0429** |
| | | | (0.0161) | (0.0151) |
| BJP voteshare | | | -0.0154 | -0.00918 |
| | | | (0.00994) | (0.00974) |
| Victory Margin | | | -0.00741 | 0.00229 |
| | | | (0.0128) | (0.0138) |
| # of candidates | | | 0.000111 | 0.000229 |
| | | | (0.000456) | (0.000468) |
| Turnout | | | 0.0144 | 0.0113 |
| | | | (0.0200) | (0.0193) |
| Constituency FE | | Yes | Yes | Yes |
| Year FE | | Yes | Yes | |
| Phase-year FE | | | | Yes |
| Constant | 0.0141*** | 0.000597 | 0.00227 | 0.00189 |
| | (0.00167) | (0.00157) | (0.0171) | (0.0183) |
| *N* | 1374 | 1374 | 1373 | 1365 |
| $R^2$ | 0.007 | 0.756 | 0.766 | 0.773 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* In all panels, Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, and turnout, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Standard errors have been clustered by constituency for all models except for the OLS model.

Table A.4: Differentiated effects of EVMs for the Left in and out of strongholds

(a) **Left in West Bengal, Kerala, and Tripura**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| EVM | 0.0380 | -0.0400 | -0.0421$^{+}$ | -0.0497$^{*}$ |
| | (0.0301) | (0.0252) | (0.0219) | (0.0209) |
| INC voteshare | | | -0.264$^{+}$ | -0.221 |
| | | | (0.145) | (0.133) |
| BJP voteshare | | | -0.182$^{+}$ | -0.175$^{+}$ |
| | | | (0.104) | (0.100) |
| Victory Margin | | | 0.208$^{*}$ | 0.162 |
| | | | (0.0938) | (0.108) |
| # of candidates | | | -0.000757 | 0.000581 |
| | | | (0.00318) | (0.00328) |
| Turnout | | | 0.261 | 0.122 |
| | | | (0.475) | (0.457) |
| Constituency FE | | Yes | Yes | |
| Year FE | | Yes | Yes | |
| Phase-year FE | | | | Yes |
| Constant | 0.377$^{***}$ | 0.445$^{***}$ | 0.389 | 0.483 |
| | (0.0175) | (0.0108) | (0.301) | (0.297) |
| $N$ | 192 | 192 | 192 | 192 |
| $R^2$ | 0.009 | 0.918 | 0.926 | 0.929 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(b) **Left outside West Bengal, Kerala, and Tripura**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| EVM | -0.00171 | 0.00635 | 0.00565 | 0.00900 |
| | (0.00401) | (0.00589) | (0.00657) | (0.00791) |
| INC voteshare | | | -0.0458$^{**}$ | -0.0502$^{**}$ |
| | | | (0.0146) | (0.0162) |
| BJP voteshare | | | -0.0260 | -0.0267 |
| | | | (0.0212) | (0.0235) |
| Victory Margin | | | -0.00858 | -0.0207 |
| | | | (0.0227) | (0.0223) |
| # of candidates | | | 0.000239 | -0.000161 |
| | | | (0.000560) | (0.000559) |
| Turnout | | | -0.0398 | -0.0527 |
| | | | (0.0443) | (0.0396) |
| Constituency FE | | Yes | Yes | |
| Year FE | | Yes | Yes | |
| Phase-year FE | | | | Yes |
| Constant | 0.0203$^{***}$ | 0.0176$^{***}$ | 0.0588$^{+}$ | 0.0796$^{*}$ |
| | (0.00225) | (0.00225) | (0.0338) | (0.0311) |
| $N$ | 1437 | 1437 | 1436 | 1409 |
| $R^2$ | 0.000 | 0.675 | 0.679 | 0.688 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* In all panels, Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, and turnout, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Standard errors have been clustered by constituency for all models except for the OLS model.

Table A.5: Effect of NOTA introduction in 2014 on minor party vote shares

| | (1) < 2.5% | (2) < 5% | (3) < 7.5% | (4) < 10% |
|---|---|---|---|---|
| NOTA introduction | -0.0122*** | -0.0127*** | -0.0151** | -0.0118+ |
| | (0.00252) | (0.00375) | (0.00533) | (0.00668) |
| INC voteshare | 0.00235 | -0.00792 | -0.0207 | -0.0387+ |
| | (0.00908) | (0.0125) | (0.0164) | (0.0213) |
| BJP voteshare | -0.00856 | -0.00507 | -0.0131 | -0.0289 |
| | (0.0105) | (0.0162) | (0.0231) | (0.0284) |
| Victory Margin | -0.00912 | 0.00337 | 0.0414+ | 0.0493+ |
| | (0.0104) | (0.0152) | (0.0222) | (0.0297) |
| # of candidates | 0.00240*** | 0.00252*** | 0.00270*** | 0.00301*** |
| | (0.000351) | (0.000421) | (0.000748) | (0.000770) |
| Turnout | 0.0320 | -0.0546 | -0.0876+ | -0.166** |
| | (0.0242) | (0.0350) | (0.0450) | (0.0591) |
| Constituency FE | Yes | Yes | Yes | Yes |
| Constant | 0.00676 | 0.0921*** | 0.148*** | 0.253*** |
| | (0.0184) | (0.0258) | (0.0343) | (0.0432) |
| $N$ | 1086 | 1086 | 1086 | 1086 |
| $R^2$ | 0.832 | 0.796 | 0.758 | 0.730 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*. This table shows the impact of the introduction of a NOTA option on the vote share of minor parties in Lok Sabha electoral constituencies. Each column looks at a specific definition of minor party, controls for election specific variables, and includes constituency fixed effects.

Table A.6: The moderated effect of EVMs on minor party vote shares by invalid vote rates in 1998

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $< 2.5\%$ | $< 5\%$ | $< 7.5\%$ | $< 10\%$ |
| EVM | $0.00103^{+}$ | $0.0145^{+}$ | 0.0148 | 0.0172 |
| | (0.00546) | (0.00770) | (0.0101) | (0.0150) |
| EVM*Invalid98 | 0.226 | $0.583^{+}$ | $1.001^{+}$ | 0.187 |
| | (0.304) | (0.335) | (0.524) | (0.772) |
| Year FE | Yes | Yes | Yes | Yes |
| Constituency FE | Yes | Yes | Yes | Yes |
| Year*Invalid98 | Yes | Yes | Yes | Yes |
| Constant | $0.290^{***}$ | $0.504^{***}$ | $0.501^{***}$ | $0.858^{***}$ |
| | (0.00145) | (0.00212) | (0.00272) | (0.00324) |
| $N$ | 1629 | 1629 | 1629 | 1629 |
| $R^2$ | 0.623 | 0.615 | 0.575 | 0.550 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on minor party vote shares in Lok Sabha electoral constituencies, moderated by invalid vote rates as recorded in 1998. Each column reports results for a different measure of minor candidate. Standard errors have been clustered by constituency for all models.

### A.7.2 Other Tables

Table A.7: Effect of EVMs on valid votes

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | 37587.5*** | 13693.7 | 19611.9+ | 21811.9+ | 21793.0 |
| | (5611.8) | (11213.4) | (11801.8) | (11495.78) | (18052.1) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-Year FE | | | | Yes | |
| Constant | 675191.1*** | 760420.1*** | 564393.8*** | 560744.5*** | 567489.2*** |
| | (6338.7) | (2469.2) | (62507.41) | (66407.9) | (7037.4) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.012 | 0.926 | 0.931 | 0.941 | 0.968 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on valid votes in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score, the invalid vote rate and total number of electors, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.8: Effect of EVMs on vote share of candidates receiving less that 0.5% of votes

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | 0.000887** | -0.00274** | 0.000608 | 0.000724 | -0.00247 |
| | (0.000324) | (0.00105) | (0.000929) | (0.000957) | (0.00160) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.00754*** | 0.000908*** | -0.0130*** | -0.0115*** | 0.0117*** |
| | (0.000243) | (0.000229) | (0.00267) | (0.00309) | (0.000714) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.003 | 0.642 | 0.823 | 0.828 | 0.634 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on the vote share of candidates receiving less than 0.5% of vote share in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and total number of electors, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.9: Effect of EVMs on vote share of candidates receiving less that 20% of votes

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | 0.0231*** | 0.0237 | 0.00537 | 0.00445 | 0.0317 |
| | (0.00432) | (0.0164) | (0.0130) | (0.0135) | (0.0193) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.111*** | 0.0507*** | 0.456*** | 0.440*** | 0.0580*** |
| | (0.00349) | (0.00347) | (0.0495) | (0.0563) | (0.00831) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.012 | 0.582 | 0.715 | 0.726 | 0.555 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on the vote share of candidates receiving less than 20% of vote share in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and total number of electors, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.10: Effect of EVMs on minor party vote shares in subsamples of the data

(a) Proximate constituency subsample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | < 2.5% | < 5% | < 7.5% | < 10% |
| EVM | 0.0150** | 0.0184* | 0.0269* | 0.00763 |
| | (0.00523) | (0.00811) | (0.0100) | (0.0144) |
| Constituency FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Constant | 0.0230*** | 0.0208*** | 0.0201*** | 0.0520*** |
| | (0.00180) | (0.00270) | (0.00375) | (0.00574) |
| *N* | 144 | 144 | 144 | 144 |
| $R^2$ | 0.582 | 0.562 | 0.461 | 0.393 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(b) Matched constituencies subsample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | < 2.5% | < 5% | < 7.5% | < 10% |
| EVM | 0.0192** | 0.0257*** | 0.0313** | 0.00510 |
| | (0.00592) | (0.00665) | (0.0104) | (0.0154) |
| Constituency FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Constant | 0.0346*** | 0.0467*** | 0.0667*** | 0.0739*** |
| | (0.00273) | (0.00388) | (0.00415) | (0.00625) |
| *N* | 162 | 162 | 162 | 162 |
| $R^2$ | 0.502 | 0.610 | 0.567 | 0.452 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* Panel (a) conducts a basic diff-in-diff regression of all measures of minor party vote share on EVM within the proximate constituency subsample, Panel (b) conducts a basic diff-in-diff regression of all measures of minor party vote share on EVM within the matched constituency subsample. All standard errors have been clustered at the constituency level.

Table A.11: Propensity score matching results

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | < 2.5% | < 5% | < 7.5% | < 10% |
| EVM | 0.0156** | 0.0218*** | 0.0307*** | 0.0114 |
| | (0.00391) | (0.00587) | (0.00893) | (0.0106) |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the results from one-to-one propensity score matching. Each column shows the effect estimated through the matching procedure for each measure of minor party.

Table A.12: Effects of EVMs on HHI

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | -0.00331 | -0.0148 | -0.0274** | -0.0252* | -0.0179 |
| | (0.00287) | (0.0106) | (0.0103) | (0.0107) | (0.0170) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.390*** | 0.399*** | 0.384*** | 0.395*** | 0.457*** |
| | (0.00289) | (0.00238) | (0.0285) | (0.0323) | (0.00521) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.000 | 0.690 | 0.760 | 0.765 | 0.568 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on the HHI in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory and turnout rate, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.13: Effect of EVMs on turnout

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | -0.0346*** | -0.0238** | -0.0219* | -0.0177* | -0.0140 |
| | (0.00326) | (0.00854) | (0.00883) | (0.00817) | (0.0108) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.619*** | 0.727*** | 0.741*** | 0.766*** | 0.465*** |
| | (0.00404) | (0.00238) | (0.0193) | (0.0203) | (0.00509) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.024 | 0.847 | 0.849 | 0.873 | 0.908 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on turnout rates in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, and the HHI score, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.14: Results from subsamples of the data

(a) Invalid rate

| | (1) Proximate constituencies | (2) Matched constituencies |
|---|---|---|
| EVM | -0.0122*** | -0.0192*** |
| | (0.00281) | (0.00428) |
| Constituency FE | Yes | Yes |
| Year FE | Yes | Yes |
| Constant | 0.0240*** | 0.0166*** |
| | (0.00141) | (0.00122) |
| $N$ | 144 | 162 |
| $R^2$ | 0.719 | 0.704 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(b) Turnout

| | (1) Proximate constituencies | (2) Matched constituencies |
|---|---|---|
| EVM | -0.00758 | 0.000777 |
| | (0.0107) | (0.0165) |
| Constituency FE | Yes | Yes |
| Year FE | Yes | Yes |
| Constant | 0.467*** | 0.533*** |
| | (0.00608) | (0.00621) |
| $N$ | 144 | 162 |
| $R^2$ | 0.930 | 0.931 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* Panel (a) conducts a basic diff-in-diff regression of invalid rates on EVM within two subsamples of the data, Panel (b) conducts a basic diff-in-diff regression of HHI on EVM within two subsamples of the data, Panel (c) conducts a basic diff-in-diff regression of invalid rates on EVM within two subsamples of the data. All standard errors have been clustered at the constituency level.

Table A.15: Effect of EVM*criminal constituency on turnout

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | -0.0265*** | -0.0272+ | -0.0256+ | -0.0177 | -0.00839 |
| | (0.00652) | (0.0155) | (0.0150) | (0.0132) | (0.0123) |
| EVM*criminal constituency | -0.0139** | 0.00565 | 0.00636 | 0.000243 | -0.0108 |
| | (0.00647) | (0.0184) | (0.0177) | (0.0160) | (0.0143) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Year*criminal constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.636*** | 0.624*** | 0.647*** | 0.670*** | 0.469*** |
| | (0.00634) | (0.00409) | (0.0222) | (0.0246) | (0.00797) |
| $N$ | 1629 | 1629 | 1628 | 1601 | 252 |
| $R^2$ | 0.0510 | 0.849 | 0.851 | 0.876 | 0.908 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on turnout rates in constituencies that had a criminal candidate run in 2004. Column (1) runs a simple OLS model, Column (2) reports the results of a triple differences regression with constituency specific fixed effects, electoral year fixed effects, and an interaction of year dummies and criminal constituency dummy, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and turnout rate, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts the triple difference regression on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.16: Effect of EVM on vote share of candidate placed 1st on the ballot list in the Hindi belt

| | (1) | (2) | (3) |
|---|---|---|---|
| EVM | -0.0130 | -0.000638 | -0.0483 |
| | (0.0128) | (0.0767) | (0.0794) |
| Year FE | | Yes | Yes |
| Constituency FE | | Yes | Yes |
| Controls | | | Yes |
| Constant | 0.249*** | 0.138*** | 0.253 |
| | (0.00998) | (0.0260) | (0.155) |
| $N$ | 675 | 675 | 674 |
| $R^2$ | 0.001 | 0.520 | 0.549 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on the vote share of the 1st placed candidate in the Hindi belt. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and the turnout rate. Standard errors are clustered at the constituency level.

Table A.17: Effect of EVM on vote share of candidate placed below the eventual winner on the ballot list in the Hindi belt

| | (1) | (2) | (3) |
|---|---|---|---|
| EVM | -0.00854 | -0.0313 | -0.0313 |
| | (0.0111) | (0.0520) | (0.0569) |
| Year FE | | Yes | Yes |
| Constituency FE | | Yes | Yes |
| Controls | | | Yes |
| Constant | $0.109^{***}$ | 0.0262 | -0.0995 |
| | (0.00801) | (0.0192) | (0.145) |
| $N$ | 651 | 651 | 650 |
| $R^2$ | 0.001 | 0.454 | 0.480 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on the vote share of the candidate placed below the winner in the Hindi belt. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and the turnout rate. Standard errors have been clustered at the constituency level.

Table A.18: Effect of EVM on vote share of candidate placed above the eventual winner on the ballot list in the Hindi belt

| | (1) | (2) | (3) |
|---|---|---|---|
| EVM | -0.0271$^{*}$ | 0.0165 | 0.0355 |
| | (0.0135) | (0.0727) | (0.0690) |
| Year FE | | Yes | Yes |
| Constituency FE | | Yes | Yes |
| Controls | | | Yes |
| Constant | 0.137$^{***}$ | 0.0882$^{**}$ | -0.0264 |
| | (0.00974) | (0.0273) | (0.183) |
| $N$ | 499 | 499 | 498 |
| $R^2$ | 0.007 | 0.587 | 0.629 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*. This table shows the impact of EVMs on the vote share of the candidate placed below the winner in the Hindi belt. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and the turnout rate. Standard errors have been clustered at the constituency level.

Table A.19: Effect of EVMs on state incumbent vote share

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| EVM | 0.00162 | 0.000623 | -0.00332 | -0.00709 | -0.00454 |
| | (0.00183) | (0.00479) | (0.00482) | (0.00498) | (0.00751) |
| Year FE | | Yes | Yes | | Yes |
| Constituency FE | | Yes | Yes | Yes | Yes |
| Controls | | | Yes | Yes | |
| Phase-year FE | | | | Yes | |
| Constant | 0.0429*** | 0.0785*** | 0.104*** | 0.0922** | 0.0322*** |
| | (0.00166) | (0.00134) | (0.0253) | (0.0298) | (0.00309) |
| *N* | 1617 | 1617 | 1616 | 1589 | 243 |
| $R^2$ | 0.000 | 0.621 | 0.682 | 0.693 | 0.595 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on state incumbent vote share in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and turnout rate, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.20: Effect of VVPAT on turnout

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VVPAT | -0.0235 | 0.0195 | 0.0234 | 0.0112 |
| | (0.0339) | (0.0391) | (0.0344) | (0.0624) |
| Year FE | | Yes | Yes | Yes |
| Constituency FE | | Yes | Yes | Yes |
| Controls | | | Yes | |
| Constant | $0.634^{***}$ | $0.720^{***}$ | $0.649^{***}$ | $0.532^{***}$ |
| | (0.00510) | (0.00186) | (0.0174) | (0.00895) |
| $N$ | 1086 | 1086 | 1086 | 75 |
| $R^2$ | 0.000 | 0.944 | 0.954 | 0.929 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on invalid vote rates in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and turnout rate. Finally, Column (4) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.21: Effect of VVPAT on state incumbent vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VVPAT | -0.00880$^{*}$ | 0.000552 | -0.00144 | -0.00269 |
| | (0.00438) | (0.00591) | (0.00493) | (0.0100) |
| Year FE | | Yes | Yes | Yes |
| Constituency FE | | Yes | Yes | Yes |
| Controls | | | Yes | |
| Constant | 0.0228$^{***}$ | 0.0351$^{***}$ | 0.0245$^{*}$ | 0.0315$^{***}$ |
| | (0.000868) | (0.000519) | (0.0119) | (0.00220) |
| $N$ | 1078 | 1078 | 1078 | 73 |
| $R^2$ | 0.001 | 0.851 | 0.889 | 0.773 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes.* This table shows the impact of EVMs on invalid vote rates in Lok Sabha electoral constituencies. Column (1) runs a simple OLS model, Column (2) reports the results of a basic diff-in-diff regression with constituency specific fixed effects and electoral year fixed effects, Column (3) includes time-varying control variables such as the INC vote share, BJP vote share, number of candidates in the constituency, the eventual margin of victory, the HHI score and turnout rate, Column (4) replaces electoral year fixed effects by phase-year fixed effects. Finally, Column (5) conducts a basic diff-in-diff regression with constituency and year fixed effects on constituencies with more than 40% of its population living in urban areas. Standard errors have been clustered by constituency for all models.

Table A.22: Leads of the treatment

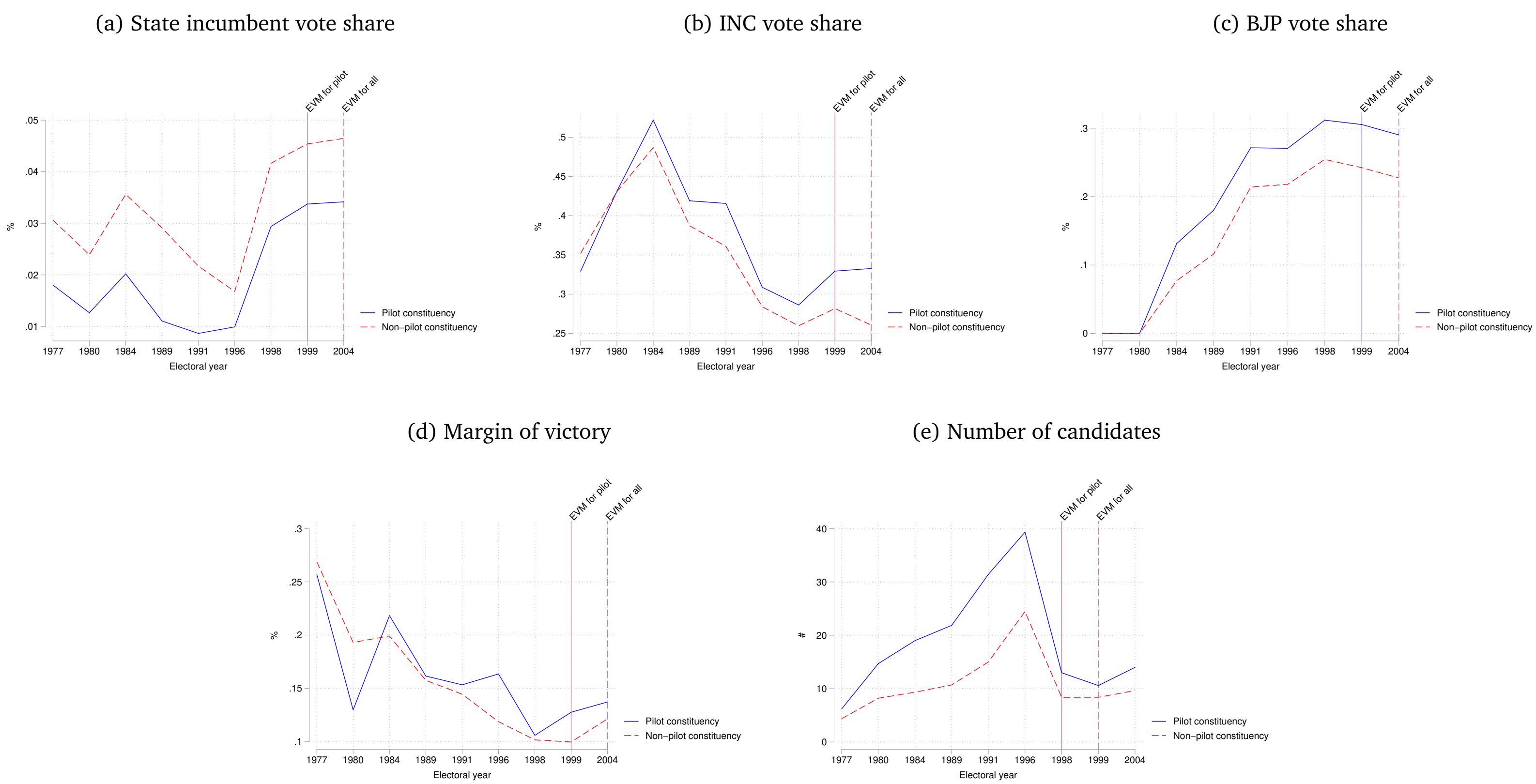
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable | Invalid votes | HHI | Turnout | 2.5% | 5% | 7.5% | 10% |
| Pilot*1989 | -0.00265 | -0.00527 | -0.0215$^{+}$ | -0.000447 | 0.00387 | 0.00577 | 0.0114 |
| | (0.00386) | (0.0182) | (0.0113) | (0.00414) | (0.00621) | (0.00807) | (0.0132) |
| Pilot*1991 | 0.00125 | 0.00381 | -0.0718$^{***}$ | -0.00326 | 0.00683 | 0.00399 | -0.00297 |
| | (0.00279) | (0.0186) | (0.0183) | (0.00431) | (0.00725) | (0.00844) | (0.0118) |
| Pilot*1996 | 0.000881 | 0.00234 | -0.0399$^{*}$ | -0.00575 | -0.00177 | 0.00932 | 0.00627 |
| | (0.00267) | (0.0153) | (0.0165) | (0.00538) | (0.00895) | (0.0118) | (0.0138) |
| Pilot*1998 | 0.00134 | 0.00503 | -0.0445$^{**}$ | -0.00378 | -0.00123 | -0.00262 | -0.0000735 |
| | (0.00270) | (0.0137) | (0.0141) | (0.00463) | (0.00719) | (0.00865) | (0.0108) |
| ***Pilot*1999*** | ***-0.0131***$^{***}$ | ***-0.00490*** | ***-0.0758***$^{***}$ | ***0.00738*** | ***0.0198***$^{***}$ | ***0.0245***$^{**}$ | ***0.0182***$^{*}$ |
| | ***(0.00285)*** | ***(0.0157)*** | ***(0.0172)*** | ***(0.00476)*** | ***(0.00561)*** | ***(0.00740)*** | ***(0.00905)*** |
| Pilot*2004 | 0.00719$^{**}$ | 0.0147 | -0.0596$^{***}$ | -0.00956$^{*}$ | -0.0105 | -0.0127 | -0.00841 |
| | (0.00275) | (0.0151) | (0.0141) | (0.00442) | (0.00642) | (0.00874) | (0.0110) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constituency FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.0366$^{***}$ | 0.446$^{***}$ | 0.697$^{***}$ | 0.0299$^{***}$ | 0.0461$^{***}$ | 0.0530$^{***}$ | 0.0640$^{***}$ |
| | (0.00192) | (0.00306) | (0.00285) | (0.000850) | (0.00129) | (0.00170) | (0.00223) |
| *N* | 3777 | 3777 | 3775 | 3777 | 3777 | 3777 | 3777 |
| $R^2$ | 0.312 | 0.586 | 0.779 | 0.543 | 0.486 | 0.449 | 0.422 |

Standard errors in parentheses

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*. This table assigns placebo treatments to pilot constituencies in electoral years prior to 1999. Column (1) investigates the effect of placebo EVM treatment on invalid vote rates, Column (2) looks at the HHI, Column (3) does the same for turnout rates, and Columns (4)-(7) look at the leads of treatment for the different measures of minor party vote share. The actual treatment year for pilot constituencies is 1999, and is marked by the bold and italic row. All errors have been clustered at the constituency level.

Figure A.3: Pre-trends for other variables




(a) State incumbent vote share

(b) INC vote share

(c) BJP vote share

(d) Margin of victory

(e) Number of candidates

*Notes.* The blue solid line plots the average values of the different variables in all pilot constituency across election years while the red dashed line plots the average of the control variables in non-pilot constituencies. The year 1998 marks the last election before the introduction of EVMs. Thus, 1999 is the first post-treatment year for the pilot constituencies. In the year 2004, the non-pilot constituencies also used EVMs.

# References


Ahuja, Amit and Pradeep Chhibber. 2012. "Why the poor vote in India:"If I don't vote, I am dead to the state"." *Studies in comparative international development* 47(4):389–410. 7

Aidt, Toke, Miriam A Golden and Devesh Tiwari. 2011. "Incumbents and criminals in the indian national legislature." https://www.repository.cam.ac.uk/bitstream/handle/1810/242058/cwpe1157.pdf?sequence=1&isAllowed=y. 11

Alvarez, R Michael, Melanie Goodrich, Thad E Hall, D Roderick Kiewiet and Sarah M Sled. 2004. "The complexity of the California recall election." *Political Science and Politics* 37(01):23–26. 2, 6

Banerjee, Mukulika. 2015. *Why India Votes?* Routledge. 6

Dee, Thomas S. 2007. "Technology and voter intent: Evidence from the California recall election." *The Review of Economics and Statistics* 89(4):674–683. 2

Ho, Daniel E and Kosuke Imai. 2008. "Estimating causal effects of ballot order from a randomized natural experiment the California alphabet lottery, 1978–2002." *Public Opinion Quarterly* 72(2):216–240. 2, 6

Kohno, Tadayoshi, Adam Stubblefield, Aviel D Rubin and Dan S Wallach. 2004. Analysis of an electronic voting system. In *Security and Privacy, 2004. Proceedings. 2004 IEEE Symposium on*. IEEE pp. 27–40. 10

Krosnick, Jon A, Joanne M Miller and Michael P Tichy. 2003. "An unrecognized need for ballot reform: The effects of candidate name order on election outcomes." *Rethinking the vote: The politics and prospects of American election reform* pp. 51–73. 6

Kumar, Sanjay and Ekta Walia. 2011. "Analysis of electronic voting system in various countries." *International Journal on Computer Science and Engineering* 3(5):1825–1830. 3, 9

Rohde, David. 2004. "Maujempur Journal; On a Newfangled Voting Machine, the Same Old Fraud." *New York Times* . 11

Stewart, Charles. 2011. "Voting technologies." *Annual Review of Political Science* 14:353–378. 9

Vaishnav, Milan. 2017. "When Crime Pays: Money and Muscle in Indian Politics.". 11

Wolchok, Scott, Eric Wustrow, J Alex Halderman, Hari K Prasad, Arun Kankipati, Sai Krishna Sakhamuri, Vasavya Yagati and Rop Gonggrijp. 2010. Security analysis of India's electronic voting machines. In *Proceedings of the 17th ACM conference on Computer and communications security*. ACM pp. 1–14. 3, 8