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Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India[1]

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Abstract: The recent increase in the number of criminally accused politicians elected to state assemblies has caused much furor in India. Despite the potentially important consequences and the widely divergent views, the implications of their elections to state legislative assemblies on constituency-level economic performance are unknown. Using a regression discontinuity design and data on the intensity of night lights in satellite imagery at the constituency level, our results suggest that the cost of electing criminally accused politicians on measures of economic activity is quite large. Using estimates of the elasticity of GDP to light, we find that the election of criminally accused candidates lead to roughly 5 percent lower GDP growth per year on average. These estimated costs increase for candidates with serious accusations, multiple accusations, and accusations regarding financial crimes. Our result survives variety of robustness checks.

Keywords: Growth, Indian Politicians, Information disclosure, Regression Discontinuity, India

JEL Codes: D72, D73, O40, O12

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"Earlier politicians used criminals. Now the criminals themselves have entered politics" - (Associated Press, 2014)

1 Introduction

India is home to the world's largest and the most vibrant democracy, with multiple parties and free elections. At the same time, a very large portion of elected officials have open criminal cases against them. This is contrary to what economic theory predicts, where competitive legislative elections are supposed to prevent criminal or venal candidates from winning or retaining office (Ferraz and Finan, 2011). However, in India, not only are criminally accused politicians elected but this number has steadily increased over time.[1,2] According to the NY Times (2014), the percentage of elected politicians who have open criminal accusation rose from 24 percent in 2004 to 30 and 34 percent in 2009 and 2014 respectively.[3]

With an open and transparent democratic federal structure, India has publicly available information regarding criminally accused representatives.[4] Consequently, the continued election of such candidates to the national Parliament and state legislative assemblies is not just surprising. While this has been widely discussed, the actual economic costs are unknown to social scientists. It has been well established that political considerations affect the distribution of government transfers, public spending (Albouy, 2009; Ansolabehere and Snyder, 2006; Finan, 2004; Besley et al., 2004) and firms are likely to receive benefits and loans when they are connected to a politician.[5] Whether the election of criminally accused politicians to

[1] An analysis of 541 of the 543 winning candidates in the 2014 Parliamentary elections in India by National Election Watch (NEW) and Association for Democratic Reforms (ADR) suggests that they may even have disproportionate chance to be elected. A candidate with criminal cases had 13% chance of winning in the 2014 Lok Sabha (Lower House of the Parliament) election whereas it was 5% for an aspirant with a clean record.

[2] On a constituency-wise basis, 35 percent of all state assembly constituencies (and 45 percent of parliamentary constituencies) feature at least one candidate under serious indictment. Indicted politicians have a 2:1 advantage in terms of winning election, irrespective of the severity of the charges (Vaishnav, 2011).

[3] Article published by Neha Thirani Bagri on May 23, 2014.

[4] It is easy to obtain information on a candidate's criminal record, thus, hiding or under-reporting pending cases is not a serious concern and therefore unlikely to influence elections.

[5] The links between politicians and firms has been widely studied by economists. For example, Khwaja

public offices has impacts on measures of economic activity remains an unanswered empirical question.

Criminality is a well-established problem in India's politics, and all of the major political parties are implicated. The full scope of the problem was not known until after 2003, after public interest litigation by the Association for Democratic Reforms (ADR), an election watchdog, candidates were required to file public disclosures of their backgrounds including any open criminal cases.[6] Although the phenomenon of "criminal" politicians has been widely publicized, we know very little about the costs of electing such candidates to public offices, whether in India or elsewhere in the developing world. In particular, the constituency level costs, which determine the incentives for and costs of electing such candidates, have not been previously studied.[7]

Three broad explanations have been proposed for the costs of electing criminally accused politicians.

"Every dollar that a corrupt official or a corrupt business person puts in their pocket is a dollar stolen from a pregnant woman who needs health care; or from a girl or a boy who deserves an education; or from communities that need water, roads, and schools. Every dollar is critical if we are to reach our goals to end extreme poverty by 2030 and to boost shared prosperity." - Jim Yong Kim (World Bank President)

The first set of explanations argues that criminally accused politicians are more likely to be criminals and that this adversely affects constituencies. This view is supported by studies which find that voters rejected alleged criminal or corrupt candidates (Banerjee et al., 2014).

and Mian (2005) find that 23% of firms that received corporate loans in Pakistan had a politician sitting on their board. Fisman (2001) finds that 38% of firms on the Jakarta stock exchange were closely connected to President Suharto. Faccio et al. (2006) finds that 87% of market capitalization in Russia is in politically connected firms.

[6]For the detailed discussion of the Supreme Court of India judgement see: `http://adrindia.org/sites/default/files/Supreme_Court's_judgement_2nd_May_2002.pdf`

[7]Asher and Novosad (2013) examine the benefit of having a local politician who is aligned with the party in power of the state government on private sector employment in India. Similarly Sukhtankar (2012) finds that politicians extract rents from firms in order to further their personal electoral goals in the context of state of Maharashtra in India.

Substantial evidence also supports the idea that criminally accused politicians may have a harmful effect. Corruption, especially regarding public servants, is an ancient problem.[8] Corruption has its adverse effects not just on static efficiency but also on investment and growth (Bardhan, 1997). Taking the example of corruption, it has been declared "public enemy number one" by the World Bank and has been linked to lower economic growth, levels of per capita GDP level and Human Development Index scores (Mauro, 1995; Shleifer and Vishny, 1993; Gyiman-Brembong, 2002; Dreher and Herzfield, 2005; Kaufmann, 2002; Rose-Ackerman and Truex, 2012; Olken and Pande, 2012). In the context of India, corruption is not only large in magnitude but also widely pervasive. Recent cases have reported figures of US $29 billion in the 2010 2G spectrum case and US $31 billion for the "Coalgate" scandal between 2004 and 2009. Corruption is sufficiently widespread that the marginal rate of corruption associated with a statutory wage increase in a nationwide scheme (NREGA) was close to 100 percent (Niehaus and Sukhtankar, 2013).[9] Recent evidence suggests that corruption is not limited to bureaucrats but also extends to elected representatives (Fisman et al., forthcoming).

"In India's Politics, Jail Time Is a Badge of Honor." - (NY Times, 2014)

A second set of explanations argues that criminally accused politicians are more likely to be criminals but that this is a desired characteristic for voters. Whereas proponents of the first view believe that criminals lead to worse outcomes, supporters of the second view believe that the opposite is true. This might happen for different reasons. Voters may see criminals as being more efficient at finding ways to get money out of the central government (The Star, 2014). In a rapidly growing country with an often centralized allocation of (insufficient) resources, politicians may be able to influence their allocation. For instance, looking at a different aspect of candidates, Nagavarapu and Sekhri (2014) find evidence of

[8] Corruption in public administration was documented dating back to the fourth century B.C. in India in Kautiliya's Arthasastra.

[9] While obviously very high, reports in other countries find rates varying from 18 to 87 percent (Reinikka and Svensson, 2004; Olken, 2006; Chaudhury et al., 2006; Olken 2007; and Ferraz et al., 2012.).

regulatory capture since national candidates are able to channel more electricity to their constituencies than do regional candidates.

A closely related idea is that voters may prefer criminal candidates because of patronage. Criminal candidates are both willing and able to make side payments (Wade 1985). In the context of caste-line voting in India, this suggests that criminal candidates may particularly benefit their voters although potentially at some cost for the constituency.[10] In this way, this nuanced view combines both the first and second set of explanations.

"They may protest the administrative machinery and thereby break the law, but they are seen as local heroes who are trying to help poor people by different means" - (NY Times, 2014)

Our analysis is further complicated by a third view which notes that some of the criminally accused candidates may be local "Robin Hoods". Whereas supporters of the first and second view generally agree that the criminally accused candidates are actually criminals, supporters of the third view believe that some of these "crimes" are committed on behalf of the people and therefore that the candidates are not true criminals. For instance, Jaffrerot and Verniers (2014) argue that some cases of criminal behavior are just the result of involvement in democratic protest movements. They note that most - if not all - of the criminal charges against the two candidates with the highest totals (380 and 382 respectively) were due to protests against nuclear power.

If (some of) these candidates are in fact "Robin Hoods", this suggests that the effect of criminally accused candidates on constituency level outcomes remains an open empirical question. As the proportion of "Robin Hoods" increases, the effect of criminally accused politicians should tend towards zero and eventually lead to positive outcomes.

One potential problem is that the impact of criminally accused candidates on light output (and proxy for economic growth) is likely to be endogenous to the outcome variable of interest. In particular, the constituencies that elect criminally accused candidates may differ

[10]Vaishnav (2011) argues that criminally indicted politicians benefit parties when they can exploit social divisions to build a compelling case that their criminality gives them an advantage in serving the interests of their fellow co-ethnics.

in unobserved ways from constituencies that elect candidates who are not criminally accused. In this paper, we use a regression discontinuity design (RDD), and compare constituencies in which a criminally accused candidates barely won with constituencies in which a criminally accused candidate barely lost (to a non-criminally accused candidate) in state assembly elections in India between 2004 and 2008. The underlying assumption is that if these elections are close enough to swing for either candidate, they provide nearly random variation in the identity of the winning candidate (Lee, 2008; Lee and Lemieux, 2010). The use of an RDD design to resolve endogeneity in elections is not novel in the context of India as it has been exploited by several recent studies (Asher and Novosad, 2013; Fisman et al., forthcoming; Bhalotra et al., 2013; Bhalotra et al., 2013; Clots-Figueras, 2012; Bhalotra and Clots-Figueras, 2014; Uppal, 2009).

Our main findings indicate that at the cutoff criminally accused candidates who are elected have a causal and strong negative impact on the growth of night light at the constituency level. Using global (Henderson et al. 2012) and India-specific (Bickenbach et al. 2013) estimates of the elasticity of GDP to night light, we find that criminally accused candidates lead to an average 2.7% to 7.6% lower GDP growth per year. Using an average GDP growth rate of 6% per year, the findings show that yearly growth was 0.29 to 0.81 GDP points lower per year.

This study is of interest for several reasons. Foremost, we present the first quantitative estimates of the economic costs of electing criminally accused politicians to state assemblies by focusing at the constituency level economic growth. The results suggest strong costs to local economic growth which would likely spill over onto other outcomes such as poverty. Moreover, they highlight a potential cost associated with the election of lower quality (or criminal) candidates in democracies. Since there is no time series data of economic growth at the constituency level, we use the intensity of night lights in satellite imagery as a proxy for local economic growth. Additionally, our paper also contributes to an emerging literature on how various political factors affect distribution of night lights in India. Baskaran, Min and Uppal (2014) find that in special elections to state legislative Assemblies held to fill midterm vacancies electricity provision increases just before elections. The electricity targeting appears more pronounced in swing races and where government majority is at stake.

To test the robustness of our main findings and due to the specific context in India, we further examine different definitions of "criminal" accusations. This is especially important because court cases in India can take decades, opposing candidates may have incentives to file false cases against each other.[11] We first, use "serious" charges and show that our main findings are not only significant but of larger magnitude. The choice of "serious" charges is motivated by several reasons. As noted earlier, democratic reformers tend to be accused of less serious charges such as unlawful assembly, civil disobedience, electioneering, etc. Additionally, clearly not all accusations (if true) are likely to affect the economic outcomes in a constituency with more serious charges likely indicating a stronger effect. Additionally, insofar as it is costlier to manufacture serious charges, such as murder, kidnapping or rape, against an opposing candidate, the "serious" may be more likely to be true. We then consider different thresholds of "multiple" criminal charges. Insofar as there is cost to falsely accusing opponents, higher number of accusations should give a stronger signal. We finally consider "financial" charges, where we consider charges that causes loss to public exchequer. Once again our main findings are robust but of larger magnitude. It is important to consider various categories, because not all criminal accusations are equal when considering their impact on measures of economic activity. To sum up, our main findings are robust to these alternative definitions but the magnitude of the coefficient increases.

Taken together, our results indicate that criminally accused politicians have a strong adverse impact on constituency level growth. This is consistent with both the first view (they harm the constituency) and the more nuanced version of the second view (they harm

[11] Vaishnav (2011a) conducts three tests of political motivation and reject the hypothesis that cases are disproportionately filed against politically prominent or successful candidates.

the constituency but benefit particular voting blocks). To differentiate between these views, we investigate the distribution of night lights between constituencies which elect criminally-accused candidates and those without charges. Our admittedly crude measure of criminal status does not indicate any difference between candidate types.

The remainder of this paper is organized as follows. Section 2 provides detailed description of the institutional context. Section 3 discusses the identification strategy while section 3 describes the data. Section 5 presents the results on the costs of electing criminally accused candidates and discusses robustness. Section 6 concludes and discusses the policy implications.

2 Background

2.1 Political Institutions in India

India is a federal republic with a parliamentary system of government, where the formal political structure parallels that of the national structure. The Parliament of India consists of the President of India and the two Houses – The Upper House (also called the Rajya Sabha or Council of States) and The Lower House (also called the Lok Sabha or House of the People). Those elected or nominated to either house of the Parliament are referred to as Members of Parliament (or MPs). The states in India follow a similar structure where The Upper House is called Vidhan Parishad (or Legislative Council) and The Lower House is called the Vidhan Sabha (or Legislative Assembly). Those elected or nominated to either house of the state assembly are referred to as Member of Legislative Assembly (or MLAs).

Both federal and states are divided into a single-member constituencies and characterized by a first-past-the-post election system. That is, in each constituency, the candidate with the plurality of votes wins the elections. Elections are scheduled to take place every 5 years; although it is possible to have elections before the 5-year term mostly due to shifting of political alignments.[12]

2.2 Criminality in Indian Politics

The issue of criminally accused candidates contesting elections in India is not new. Both the Election Commission of India and the Indian Parliament have shown great concern about the increasing "criminalization" of politics, especially after the landmark judgment of the Supreme Court of India in 2003. The Association for Democratic Reforms (ADR) along with the National Election Watch have conducted Election Watches for all State and Federal elections post 2003 in India.[13]

It is widely believed that there is a criminal nexus between political parties and anti-social elements leading to increased criminalization of politics in India. In the recently concluded Lok Sabha Elections, roughly one third of the newly-elected MPs have a criminal background according to their disclosed sworn affidavits to the Election Commission of India. In total, 186 out of 543 Members of Parliament (MP) have criminal cases including serious charges of murder and rape. What is surprising is that the proportion of MPs facing criminal charges has increased between the 2009 and 2014 Lok Sabha elections.[14] The story is similar for the state legislative assembly elections. According to the ADR report, over 30% of the MLAs face criminal cases in India.

For example, in one of most populous and politically important state, Uttar Pradesh, 575 candidates for the 403 assembly seats had criminal backgrounds or faced criminal charges during the 2007 state legislative assembly elections. Out of these 403 candidates, 140 won assembly seats. Following this success, it is not surprising that an even greater number of

[12]According to the Indian Constitution, any Indian citizen who is registered as a voter and is over the age of 25 years can run for election to the Federal; Government or the State Legislative Assemblies. However, candidates running for the State Legislative Assemblies should be the resident of the same state.

[13]Election Watch comprises background reports based on Criminal, Financial, Educational and Income Tax details of Candidates and Winners (MPs, MLAs and Ministers) who have contested Elections to State Assemblies, the Parliament and a few local bodies.

[14]In 2009, 30% of the Lok Sabha members or MPs had criminal cases and this share has increased to 34% in the last concluded Lok Sabha elections in 2014.

criminally accused candidates (759) ran in the next elections in 2012. Of these, 189 won seats in the state assembly. (ADR 2012a).

Elected officials, including MPs and MLAs are widely reputed to be involved in corruption, mostly graft and embezzlement of public funds (BBC News India 2012, India Today 2012). In the case of Uttar Pradesh state legislators, the 287 elected MLAs in 2007 who ran for elections again in 2012 witnessed an increase in their average asset value from $220,613 to $658,804, over their 5 year term in office. The political affiliation was especially important as MLAs who belonged to the political party heading the state government (or the ruling party) saw their asset value increase to an average of $500,000. For opposition party members, this increase amounted to less than $300,000 (Banerjee et. al 2012).[15]

Moreover, Fisman et al. (forthcoming) utilize the asset disclosures of candidates for Indian state legislators taken at two points across a five year election cycle and compares the asset growth of election winners versus runners-up to calculate the financial returns from holding public office relative to private sector opportunities available to political candidates. The estimated annual growth rate of winners' assets is 3-5 percent higher than that of runners-up.

3 Empirical Strategy

This paper considers assembly elections held during the 2004 to 2008 period to examine whether the impact of electing a criminally accused candidate on economic performance in the constituency. We consider the following model:

$$y_{ist+1} = \alpha + \beta * CRIMINAL_{ist} + \varepsilon_{ist+1} \tag{1}$$

[15]The average annual salary of MLAs in Uttar Pradesh is approximately $12,000. The Chief Minister (elected head of the state) of Uttar Pradesh, Kumari Mayawati, saw her wealth increase $6.2 million over her five-year term from 2007–2012. Data were downloaded from National Election Watch (http://www.myneta.info), which compiles information from affidavits submitted by candidates during the nomination process.

where y_{ist+1} represents economic performance of constituency i in state s in year $t+1$. In the absence of direct measures of economic performance, we follow the literature and use the light output as a proxy. $CRIMINAL_{ist}$ is an indicator variable for treatment, which is 1 if a constituency i in state s elects an MLA with a criminal background and 0 otherwise. Also, ε_{ist+1} is the stochastic error term.

If the criminal status of an MLA was randomly assigned, constituencies that elected a non-criminal MLA will serve as a valid counterfactual for constituencies that elected a criminal MLA and we could compare average outcomes in these two types of constituencies to identify the causal effect of electing a criminal candidate:

$$E[y_{ist+1} \mid CRIMINAL_{ist} = 1] - E[y_{ist+1} \mid CRIMINAL_{ist} = 0] = \beta. \tag{2}$$

However, we doubt that the criminal status of an MLA is randomly determined. The main concern is that due to unobserved heterogeneity, constituencies with criminal candidates may not be comparable to constituencies without criminal candidates. For instance, criminal candidates may be more likely to run and win from certain constituencies than others. As a result, β does not identify the causal effect of criminal status of an MLA and is biased as the condition $E[\varepsilon_{ist+1} \mid CRIMINAL_{ist}] = 0$ does not hold.

$$\begin{gathered} E[y_{ist+1} \mid CRIMINAL_{ist} = 1] - E[y_{ist+1} \mid CRIMINAL_{ist} = 0] = \\ \beta + E[\varepsilon_{ist+1} \mid CRIMINAL_{ist} = 1] - E[\varepsilon_{ist+1} \mid CRIMINAL_{ist} = 0] \end{gathered} \tag{3}$$

We, however, exploit the discontinuity that arises in the first-past-the-post electoral systems. By the electoral law, only candidates who get the most votes and have a positive victory margin (defined as the difference in the vote shares of the winner and runner-up candidates) become elected. We compare criminal winners and criminal losers in close elections, where the winner's margin of victory is arbitrarily small and hypothesize that in such close contests election of an MLA with criminal background is decided as if it is random. In other words, constituencies in which a criminal candidate barely lost could serve as a valid counterfactual for constituencies that barely elected a criminal MLA allowing us to estimate the difference in outcomes of such constituencies as the causal effect of criminal background of an MLA. More formally, define reservation status as follows:

$$\begin{aligned} CRIMINAL_{ist} &= 1 \; if \; MARGIN_{ist} > 0 \\ &= 0 \; if \; MARGIN_{ist} < 0, \end{aligned} \tag{4}$$

where $MARGIN_{ist}$ is the margin of victory of an MLA. By construction, it is positive for a criminal MLA, the treated group, and negative for a non-criminal MLA, the control group. At a margin of zero, criminal status of an MLA changes discontinuously from non-criminal to criminal. Consider contests within a close neighborhood λ of the threshold margin of zero.

$$\begin{gathered} E[y_{ist+1} \mid 0 < MARGIN_{ist} \leq \lambda] - E[y_{ist+1} \mid -\lambda \leq MARGIN_{ist} < 0] = \\ \beta + E[\varepsilon_{ist+1} \mid 0 < MARGIN_{ist} \leq \lambda] - E[\varepsilon_{ist+1} \mid -\lambda \leq MARGIN_{ist} < 0]. \end{gathered} \tag{5}$$

The RD design argues that as λ goes to 0, i. e. as we examine closer elections, the differences between criminal and non-criminal constituencies vanish and we identify the causal effect of criminal status.

$$\lim_{\lambda \to 0^+} E[y_{ist+1} \mid 0 < MARGIN_{ist} \leq \lambda] - \lim_{\lambda \to 0^-} E[y_{ist+1} \mid -\lambda \leq MARGIN_{ist} < 0] = \beta, \tag{6}$$

which is simply the difference in the average outcomes of constituencies that barely elected a criminal MLA and constituencies that barely elected a non-criminal MLA.

4 Data

4.1 Criminal Status

Beginning in 2003, candidate contesting elections for elected bodies in India were required to submit an affidavit detailing his or her criminal background, asset information and educational qualifications to the Election Commission of India (ECI). These affidavits are publicly available on the Commission's website. The Association for Democratic Reforms (ADR), an election watchdog, has compiled information from these affidavits.[16] This data provides information about the number and type of criminal accusations against a candidate, number of convictions, total assets, both moveable and immoveable, of a candidate, a candidate's educational qualifications, and his or her profession.

While we use all of the information on candidates, we are primarily interested in the information regarding criminal accusations. In particular, we create a binary variable for whether a candidate is accused of any crime. It takes a value of 0 if MLA has any accusation and 0 otherwise.

As noted in the introduction, the data on criminal accusations may be misleading for a variety of reasons. In particular, beyond high profile political vendettas between leading politicians, the notoriously slow pace of the Indian judicial system provides an incentive for opponents to arrange for false criminal accusations. Similarly, there is no reason to believe that all types of criminal accusations (or crimes) will have a similar impact on economic performance. Even if the accusations are true, the importance of political or financial accusations is likely very different than those related to say driving. Additionally, some cases of criminal behavior are just the result of involvement in democratic protest movements.

For these reasons and others, it is important to consider different definitions of criminal accusations. If there is some cost to arranging for false criminal accusations, candidates with

[16]The ADR data is available for public use at `www.myneta.info`. A sample affidavit is included in the appendix.

higher numbers of criminal accusations are more likely to have "true" criminal accusations. That is, the veracity of the signal (criminal cases) increases with the number of cases. Consequently, we also consider an alternate definition for criminal accusation where the threshold for being coded as being criminally accused is raised to two or more crimes (irrespective of whether it is the same crime). Since this threshold is arbitrary, we also consider more restrictive threshold of 5 cases.

Similarly, we use the information on the type of crimes to separate "serious" crimes from less serious ones. Since any classification would be arbitrary, we follow the ADR classification between serious and non-serious crimes. While the full list of Indian Penal Codes (IPC) and their division between serious and non-serious are available in the online appendix, ADR divides crimes based on criteria such as the maximum punishment under the law, their violent nature, and offenses under the Prevention of Corruption Act.[17] Using this information, we create a binary variable for being accused of any serious crimes as defined by ADR. Lastly, we examine financial crimes by creating a binary variable which takes a value of 1 for any individual accused of any crimes related to corruption or financial gains from the state. By looking at the candidates accused of financial crimes, we are able to isolate candidates that are accused of crimes causing a loss to public exchequer.[18]

It is unfortunately not possible to identify which criminal accusations arise from democratic protest movements or similar activity. Since accusations arising from democratic protests are "falsely" coded as criminal activity, this would suggest that this will lead to classical measurement error and our estimates of the effects of "true" criminal accusations will be biased towards zero.[19]

Since the RD design uses criminally accused losers as the counterfactual, this implies

[17] The following is a link to an online Appendix on ADR criteria for coding serious crimes: http://adrindia.org/content/criteria-categorization-serious-criminal-cases.

[18] We consider the following IPCs as financial crimes after discussing with an ex-IPS Officer: 171B, 171E, 230–262, 272, 273, 274, 275, 276, 378–420, and 466–489D. Explanation of the particular IPCs is available on: http://adrindia.org/content/criteria-categorization-serious-criminal-cases.

[19] Vaishnav (2011a) conducts three tests of political motivation and reject the hypothesis that cases are disproportionately filed against politically prominent or successful candidates.

that the choice in the constituency where the criminally-accused MLA won was between the two types of candidates. This is not necessarily the case as constituencies may be choosing between only criminally accused candidates. We therefore restrict the sample to constituencies where the two candidates are one criminally-accused and one non-criminal accused candidate. This restricts our sample from the full 2633 constituencies for which we have data to a smaller sample of 941.[20]

4.2 Dependent Variable

While we are interested in the economic activity at the constituency level, this information is not widely available across constituencies or time. Following Henderson et al. (2012) and others, we use the intensity of night light as a proxy for economic activity. Henderson et al. (2012) and Storeygard (2014) show that there is a strong relationship between GDP and night light intensity at the sub-national level using a cross-section of countries for the world and Sub-Saharan Africa, respectively. Bickenbach et al. (2014) validate the use of the measure for India using district level data. As we describe below, the night light data is available annually and can be disaggregated at lower level administrative or political units.

The satellite images come from the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), a set of military weather satellites that have been flying since 1970 in polar orbit recording high resolution images of the entire earth each night between 20:00 and 21:30 local time. The high resolution images, captured at an altitude of 830 km above the earth, record concentrations of outdoor lights, fires, and gas flares at a fine resolution of 0.56 km and a smoothed resolution of 2.7 km. These images are available from 1992 onwards and are used to produce annual composites during a calendar year, dropping images where lights are shrouded by cloud cover or overpowered by the aurora or solar glare (near the poles), and

[20]Note that all of our results are robust to using the full sample. We choose this restricted sample since this is the implicit comparison in our RD design.

removing ephemeral lights like fires and other noise.

The result is a series of images covering the globe for each year from 1992 to 2009 (Elvidge et al. 1997, 2001). Images are scaled onto a geo-referenced 30 arc-second grid (approximately 1 km2). Each pixel is encoded with a measure of its annual average brightness on a 6-bit scale from 0 to 63. We utilize the data available on stable night lights that drop light values from pixels with unstable light signatures over time.

The satellite imagery also provide an objective source from which economic activity can be tracked. Panels A and B in Figure 1 show satellite images of Indian subcontinent in 1992 and 2009. India appears substantially more lit in 2009 than in 1992. This period immediately follows the beginning of the economic reforms in 1991. These reforms transformed an economy that was in an external debt crisis to an economy that was one of the fastest growing economies in the world. More importantly, this transformation is captured by the nighttime imagery in terms of growing light output over the same period.

Our primary dependent variable is the rate of growth of light output. This is the change in the natural log of night light intensity for the constituency between the current and previous period. As noted earlier, this has been widely accepted in the literature as a proxy for economic activity. By specifying it in this manner (i.e. the difference in natural logs), it will allow us to get a rough estimate of the impact on GDP using estimates of the elasticity of GDP growth to night light growth from the literature.

4.3 Constituencies

While the night light data begins in 1992 and the election data in 2003, we are unable to use the full data. The data on night lights needs to be aggregated up to the constituency level. While the boundaries for constituencies were fixed in 1976, these were affected by the Delimitation Act of 2002. This act constituted a delimitation commission to redraw the constituency boundaries based on the 2001 census figures. Based on the delay in compiling the necessary data and in creating the new boundaries, the first election with redrawn boundaries was only held in Karnataka in 2008. Consequently, the period between 1976 and 2008 had fixed constituencies boundaries allowing for the comparison of satellite imagery across time. Once the new boundaries were implemented, it is not possible to make comparison between the two periods. Thus, between the Court order to file affidavits in 2003 and redrawing of boundaries in 2008, we observe only 1 election per state.

Also, ADR does not compile affidavit information for elections held right after the order was passed and reports this information starting from elections held in states of Arunachal Pradesh, Maharashtra, and Orissa in 2004. The states excluded from our analysis are Andhra Pradesh, Chhattisgarh, Jammu and Kashmir, Karnataka, Madhya Pradesh, Mizoram, Rajasthan, and Sikkim. Table 1 reports the states that we include in our study, which is 20 out of a total of 28 states that held an election between 2004 and 2008. Table **??** reports descriptive statistics of the main variables we use in our analysis.

5 Empirical Results

5.1 Main Results

Visually, our primary result is apparent in Figure 2, which plots the growth of light against the margin of victory (margin) for criminally accused candidates. The growth of light is the residual from the regression of growth of light on state and year dummies. The scatter plot is local averages of growth of light in each successive interval of 0.5% of margin of victory. The solid curves are plotted non-parametrically using local linear regression which uses a rectangular kernel and a bandwidth using the optimal bandwidth criterion proposed by Imbens and Kalyanaraman (2012). Positive margins of victory indicate a constituency in which the criminally accused candidate won against a non-accused candidate while a negative margin shows that she/he was the runner-up and that the winner was not criminally accused. The criminal status changes discontinuously at margin=0.

There is a clear difference in the growth of light at the discontinuity (margin=0). This vertical difference between the red and blue lines reflects the causal effect of electing a criminally accused candidate. In particular, at the threshold, there is a clear negative effect of electing a criminally accused candidate.

Quantitatively, these estimates are reflected in Table 3 column 1, which shows the estimated effects using non-parametric fit (as in the Figure 2).[21] Criminal is a dummy variable that is 1 if a criminally accused candidate wins against a non-accused candidate and 0 if criminally accused candidate loses against a non-accused candidate. Since criminal background information is filed in an affidavit at the time of the election and light data is annual, the criminal dummy is fixed for the entire term of the election. Since light output is likely to be correlated overtime within a constituency, the standard errors are clustered at the constituency level. Also for comparison puposes, we consider specifications with and without state and year fixed effects.

In Panel A, a criminally accused MLA has a significant negative effect on growth of light in a constituency. In Panel B, we account for state and year fixed effects as the dependent variable is residuals from a regression of growth of light on state and year dummies. The estimated coefficient is slightly smaller after we account for state and year fixed effects. The effect of electing a criminally accused politician is negative and statistically significant at the 5% level. Substantively, constituencies that barely elect a criminally accused candidate experience about 25 percentage point decline in growth of light compared to constituencies in which a criminally accused candidate barely loses.

While we investigate the robustness of the results in Section 5.3, the main results indicate that criminally accused politicians have strong adverse impact on the economic growth at the constituency level, as proxied by the growth of night light intensity. In terms of the widely divergent views surrounding the debate on criminally accused politicians, this is consistent with the first view (they harm the constituency) and the more nuanced version of the second view (they harm the constituency but benefit particular voting blocks). These finding appear

[21]The procedure used to estimate the size of discontinuity is as described in Nicols (2012).

to strongly contradict the view that these candidates help the constituency. These results do not contradict the idea that certain criminally accused candidates are unfairly accused or that they may become accused as a result of helping the community (the third view). However, they do show that on average these candidates have a negative impact.

5.2 Heterogeneity in Costs of Electing Criminally Accused Politicians

Thus far, we have focused on estimating the average costs of electing criminally accused politicians around the discontinuity. In Table 4, we allow the effect to vary by various observable characteristics (Table 9 presents the parallel results using the fourth order polynomial).

First, we allow the effects to vary by the so-called BIMAROU (Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh and Uttarakhand) and Non-BIMAROU states. The reason we classify states as BIMAROU is because they have more corrupt constituencies (see Fisman et al. for detailed discussion) and they are known to have weaker institutions.[22] Since the 1980's these states have been singled out for corruption and for being dysfunctional (these are also the Hindi speaking belt). Additionally, there exists high degree of correlation between the Transparency International State-level measure and the BIMAROU classification. The estimated coefficient is presented in Table 4, column 1 for the BIMAROU states and in column 2 for the Non-BIMAROU states. As expected the size of the estimated coefficient for the BIMAROU states is larger and statistically significant in column 1 as compared to the coefficient in Table 3, column 1. However, the results are not statistically significant for Non-BIMAROU states.

We further divide the sample into non-reserved, SC, and ST constituencies. So far we have argued that it is the criminality of the politician that is driving our main results. If this is

[22] The Man Who Coined the term BIMARU: `http://www.business-standard.com/article/current-affairs/ashish-bose-the-man-who-coined-bimaru-tried-to-make-things-simple-114040701234_1.html`

true then it is worth investigating how the effects vary by types of constituencies. According to Vaishnav (2011), the criminality rate is approximately 27% in SC constituencies, 18% in ST constituencies, and 40% in non-reserved (also referred as General) constituencies. In addition, compared to non-reserved constituencies, SC/ST constituencies have a very small percentage of multiple indicted candidates competing against each other.[23] Lastly, reserved constituencies differ from non-reserved constituencies in several dimensions, including socio-economic characteristics, demographics, and plausibly rewards to holding public office could be lower.

We present the costs of electing criminally accused politicians by reservation status of constituencies in columns 3–5. It seems obvious that it is the criminality of the candidate in non-reserved constituencies that is driving our results. The estimated coefficient is larger and statistically significant for non-reserved constituencies as compared to SC and ST constituencies. However, the sample size is much smaller for SC and ST constituencies and hence we are left with lower statistical power.

For future research, it is will be worth dividing the non-reserved constituencies by candidate's caste, especially the other backward class (OBC).[24] OBCs have played an active role in Indian politics especially in the BIMARU states and their rise has been well documented by social scientists (see Routledge Handbook of Indian Politics, edited by Kohli and Singh, 2013; Jaffrelot, 2000 for detailed discussion.). Moreover, in the last two decades, Indian politicians have successfully used social engineering to create several caste groups with the OBCs category for vote-bank politics that requires further in-depth analysis.[25]

[23] According to Vaishnav (2011), roughly 17% of General constituencies exhibit criminal competition, while this number is only 6% in SC constituencies and 5% in ST constituencies.

[24] Other Backward Class (OBC) is a collective term used by the Government of India to classify castes which are educationally and socially disadvantaged. In the Indian Constitution, OBCs are described as "socially and educationally backward classes", and the Government of India is enjoined to ensure their social and educational development–for example, the OBCs are entitled to 27% reservations in public sector employment and higher education. The list of OBCs maintained by the Indian Ministry of Social Justice and Empowerment is dynamic, with castes and communities being added or removed depending on social, educational and economic factors. Under Article 340 of the Indian Constitution, it is obligatory for the government to promote the welfare of the OBCs.

[25] `http://timesofindia.indiatimes.com/india/Nitishs-social-engineering-formula-inspires-Congress/`

5.3 Validating the RDD

The main assumption of the RD design is that the characteristics of both candidates and constituencies are continuous around the discontinuity. That is, while the characteristics for criminally accused and non-accused candidates may be different over the entire sample, they should be identical at the discontinuity. While every possible characteristic cannot be examined, the available data strongly suggest that the characteristics are continuous.

We formally check for continuity of various constituency characteristics in Figure 3. In Panels (a)-(n), we compare bare criminal winners and bare criminal losers on growth of light in the prior year and on several other candidate and constituency characteristics, such as the assets and liabilities of the winner and 1st runner-up as reported in the affidavits filed with the election commission; their educational attainment; gender; electorate size in the previous election, which is the number of registered voters, and number of voters in the previous election, which is the number of registered voters who actually voted; whether a constituency was aligned with the ruling state party; and whether a constituency is reserved for Scheduled Caste (SC) or Scheduled Tribes (ST). We plot residuals from the regression of each of these variables on state dummies and hence account for state fixed effects. As for the main effects, we plot both local averages and local linear regression fits against margin of victory. These predetermined variables vary fairly continuously with margin of victory. Any apparent discontinuities are highly insignificant. The continuity of all these characteristics suggests that the causal effect of criminal status of a constituency in this paper is not an artifact of heterogeneity across criminal and non-criminal constituencies.

One further concern when an RD design is that close elections may sort candidate around the cutoff. For instance, perhaps candidates know that elections in a particular constituency are close and therefore criminally accused candidates rig the election to win. If this were the case, this would suggest that we would find a larger frequency of criminally accused candidates around the margin (since they would rig the elections and beat clean candidates).

`articleshow/11653704.cms`

This would imply that the density of the margin of victory, the running variable, would show a discontinuity at the cutoff. Figure 4 show the result of a McCrary Density test (2008) which confirms that the density of the running variable is similar immediately above and below the cutoff. Taken together these checks strongly support our use of an RD design.

5.4 Robustness Checks

This section examines the robustness of the above results. We first examine issues related to the primary variable of interest (being criminally accused). Second, we validate the main results using alternative definition of dependent variable and finally we present the main results using an alternative functional form, i.e. on a fourth-order polynomial in margin of victory and the interaction of the polynomial terms with the criminal dummy. As we show below, the results are robust to alternate definitions of the variables of interest and the alternative functional form.

5.4.1 Examining "Criminally Accused"

As discussed earlier, there are a variety of reasons to believe that the data on criminal accusations should be examined more closely. Consequently, in Table 5, we use the alternate specifications as discussed earlier. The first column uses the binary variable for any accusation for a serious crime, while the second column uses a binary variable for any accusation of a non-serious crime. We also distinguish the results by financial and non-financial crimes. The subsequent columns use progressively higher thresholds for criminal accusation, 2 and 5, respectively.

While the results presented in Table 5 show that our results are robust to different specifications of being criminally accused, they also raise the question about what type of criminal accusations matter? That is, should all accused candidates be regarded in the same manner or does the type of accusation matter?

When we examine different types of accusations, we find that the specific charge matters greatly. For example, the estimated impact of "criminal accusations" remain significant but the magnitude of the coefficient increases when we examine the effect of "serious" accusations in column 1 or higher numbers of accusations in column 5–6. Thus, we find that certain types of accusations lead to (much) higher costs to constituencies.

However, not all accusations lead to a negative impact. In particular, when we examine candidates who have been accused of a non-serious crime (column 2) or who have been accused of a non-financial crime (column 4), not only is the estimated magnitude much smaller but also not statistically significant. This suggests that certain accusations matter more than others and underlie our primary results.

Unfortunately, the available data do not allow us to distinguish whether this is because certain accusations are more likely to be true (i.e. they are criminals) or whether they proxy for some underlying characteristic of the candidate.

5.4.2 Examining Measurement of Light

In this sub-section we examine one potential concern regarding the dependent variable. So far we have been looking at the year to year variation in the growth night light in a constituency which could potentially be influenced by year to year volatility.

We therefore consider an alternate measure where we consider the growth of light averaged over the entire period (i.e. the election term) and present the results in Table 6, column 1. We find that the growth of night light remains significant when we estimate without (Panel A) and with state and year fixed effects (Panel B) although the estimated coefficient drops.

5.4.3 Alternative Specification

In this sub-section we estimate our main results using an alternative specification. In particular, we estimate the effects using a 4^{th} order polynomial fit, where it is a 4^{th} order polynomial in the margin of victory and interactions of polynomial terms with the binary variable for being criminally accused. The polynomial is then evaluated at the threshold margin 0. This is equivalent to the estimated coefficient on the binary criminal accused variable in the RD with a parametric fit.

The main results are presented in Table 3, column 2. We further present the results for the alternate definition of criminally accused in Table 7 and for alternate measure of night light in Table 6, column 2. Finally we present the results for the heterogeneity in Table 9.

For the baseline result, we find that the point estimate decreases with the fourth of the polynomial but is not significantly different from the reported baseline coefficient (Table 3, columns 1). To sum up, our findings are robust to the estimation of this alternative functional form.

5.5 Economic Implications

As we show in the preceding sections, the negative average effect of electing criminally accused politicians is extremely robust. While we use the change in night light intensity as a proxy for economic activity, it is possible to obtain a rough estimate of the direct effect by using the elasticity for the effect of night light intensity on GDP growth. We use two alternate measures. We use the elasticity estimated by Henderson et al. (2012) (roughly 0.30) since this is the main paper on topic. Since this is a rough estimate and uses a wide variety of countries, we also use Bickenbach et al.'s (2014) India specific estimate of elasticity (0.107). These two estimates give us an upper and lower bound respectively for the effect on GDP growth.

Table 8 presents these results using the coefficient for the base results as well as from the robustness checks for the "criminally accused" variables.[26] In each case, we use the specification with state and year fixed effects which are likely more accurate. Depending on the specification, we find estimates ranging from 2.7 to 7.6 percent lower GDP growth per year. India experienced very high growth during this period. Since these are estimates of

[26]We cannot investigate the impact on alternate dependent variable since the elasticities are only available for the original dependent variable.

the yearly cost, the foregone growth over the entire term is larger as these losses compound over the full 5 year term. Using 6 percent GDP growth as a measure of the average yearly constituency growth, this would imply that on average electing a criminally accused candidate would result 5.54 to 5.84 percent GDP growth per year (as compared to the 6 percent otherwise).

This suggests that the effects of criminal candidates are not just statistical important; rather, they are very clear economic costs to their elections. As we note early, while the methodology allows for the estimation of a clear causal relationship, the estimated impact are only valid near the discontinuity. That is, these are the losses associated with the election of criminally accused politicians in very close elections. Our results do not directly outside of the particular case. In part, the effects in elections which are not close depend on what sort of criminally accused politicians present themselves.

Some argue that parties have an incentive to present "criminals" in close elections insofar as they are able to suppress the vote and influence the outcome (Aidt et al. 2012). If this is true, it would suggest that our effects are an upper-bound. At the other extreme, it might be expected that are more likely to nominate candidates to seats which are relatively uncontested (Golden and Tiwari, 2009) which would suggest that our estimates are lower bounds.

Both of these arguments relate the propensity of criminals to run (and also their type) to the ex-ante perceived probability of election. Unfortunately, we are unable to observe the ex-ante perceptions-the data only show ex-post results. While these two can differ dramatically over the entire sample, the ex-post results are likely relatively correlated with the ex-ante probabilities and therefore also with the ex-ante perceptions. We find that criminally accused candidates are more likely to be the winning candidate as the win margin increases. Moreover, the number of criminal accusations also increases with the win margin. While not conclusive, it does suggest that our results may be lower bound estimate for the overall average in the sample.

6 Conclusions

In this paper, we estimate the economic costs of electing criminally accused politicians by utilizing criminal accusations disclosure of candidates for Indian state legislatures for the state elections held between 2003 and 2008 in India. We use this unique data set to compare criminally accused candidates that barely won with criminally accused candidates that barely lost.

Our main finding suggests negative effect of electing criminally accused politicians on measures of economic activity at the constituency level in Indian states. The estimated effect is statistically significant and economically meaningful. In particular, we find that constituencies that elect criminally accused politicians experience 2.7% to 7.6% lower GDP growth per year in the Indian states.

Our results are particularly relevant for policy makers in many developed and developing countries who are grappling with similar situations. In particular, our results are well-timed with recent Supreme Court Judgement in India that bars lawmakers (elected representatives) convicted of serious crimes from serving in national and state legislatures, even if the conviction is being appealed. Also, on June 25th, 2014, the Indian Prime Minister gave directives to the federal law ministry to work out a mechanism to settle criminal and other court cases against politicians within a year, which was his commitment during the recently concluded elections.

Although Vaishnav (2011) explores the conditions under which political parties select candidates with serious criminal records to contest elections in India, we present the first quantitative estimates of the economic costs of electing criminally accused politicians to state assemblies in India at the constituency level. Since there is no time series data of economic growth at the constituency level, we use the intensity of night lights in satellite imagery as a proxy for local economic growth. The size of the estimated negative effect of electing criminally accused politicians on measures of economic activity becomes larger when we consider candidates accused of serious crimes or financial crimes, thus reinforcing the political and economic relevance of the question!

Given the high economic costs of electing criminally accused politicians in India, it will be insightful to explore the various heterogeneities and mechanisms behind the estimated negative effects. We leave this for future work.

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TABLE 1

Number of Constituencies and Election year

State Name	Number of Constituencies	Election Years*
Arunachal Pradesh	60	1999, **2004**, 2009
Assam	126	2001, **2006**, 2011
Bihar	243	2000, **2005**, 2010
Goa	40	2002, **2007**, 2012
Gujarat	182	2002, **2007**, 2012
Haryana	90	2000, **2005**, 2009
Himachal Pradesh	68	2003, **2007**, 2012
Jharkhand	81	**2005**, 2009
Kerala	140	2001, **2006**, 2011
Maharashtra	288	1999, **2004**, 2009
Manipur	60	2002, **2007**, 2012
Meghalaya	60	2003, **2008**, 2013
Nagaland	60	2003, **2008**, 2013
Orissa	147	2000, **2004**, 2009
Punjab	117	2002, **2007**, 2012
Tamil Nadu	234	2001, **2006**, 2011
Tripura	60	2003, **2008**, 2013
Uttar Pradesh	403	2002, **2007**, 2012
Uttarakhand	70	2002, **2007**, 2012
West Bengal	294	2001, **2006**, 2011
Total	2823	

*Bold years are the first election in each state in which candidates were required to file affidavits detailing criminal and financial background.

TABLE 2

Descriptive Statistics

	All Elections			Elections Within Margin<=5%		
	Criminal=1	Criminal=0	Difference	Criminal=1	Criminal=0	Difference
	Panel A: Main Outcome Variable					
Growth of Light	2.08	2.80	-0.72	-2.01	1.90	-3.92
	[75.11]	[98.14]	[2.85]	[83.29]	[87.8]	[4.85]
Observations	1,967	1,726		621	626	
	Panel B: Predetermined Variables					
Growth of Light Previous Year	16.0	30.8	-14.9†	27.9	35.4	-7.50
	[75.5]	[140.3]	[7.23]	[91.6]	[133.9]	[12.9]
Log Electorate Size Previous Election	12.0	12.1	-0.072†	12.1	12.1	0.00076
	[0.49]	[0.42]	[0.030]	[0.43]	[0.38]	[0.046]
Log Number Voted Previous Election	11.5	11.6	-0.071‡	11.6	11.6	-0.018
	[0.45]	[0.38]	[0.027]	[0.37]	[0.35]	[0.041]
Log Winner's Assets	14.9	14.9	-0.00015	14.8	15.0	-0.25
	[2.10]	[1.90]	[0.13]	[2.27]	[1.56]	[0.22]
Log Winner's Liability	7.46	6.87	0.59	8.27	7.33	0.94
	[6.59]	[6.44]	[0.43]	[6.50]	[6.34]	[0.72]
Log Runner-up's Assets	14.9	14.7	0.14	14.8	14.9	-0.14
	[2.11]	[2.15]	[0.14]	[2.30]	[1.77]	[0.23]
Log Runner-up's Liability	7.31	6.92	0.39	6.94	6.88	0.057
	[6.43]	[6.42]	[0.42]	[6.56]	[6.48]	[0.73]
Winner's Gender Previous Election	0.074	0.053	0.021	0.075	0.069	0.0063
	[0.26]	[0.22]	[0.016]	[0.26]	[0.25]	[0.029]
Runner-up's Gender Previous Election	0.070	0.048	0.022	0.057	0.044	0.013
	[0.25]	[0.21]	[0.015]	[0.23]	[0.21]	[0.025]
Runner-up's Education	2.35	2.21	0.14*	2.44	2.26	0.18
	[1.25]	[1.20]	[0.080]	[1.23]	[1.19]	[0.14]
Winner's Education	2.22	2.48	-0.26‡	2.36	2.37	-0.0063
	[1.19]	[1.15]	[0.077]	[1.15]	[1.21]	[0.13]
SC Reserved	0.11	0.13	-0.025	0.11	0.075	0.031
	[0.31]	[0.34]	[0.021]	[0.31]	[0.26]	[0.032]
ST Reserved	0.050	0.053	-0.0028	0.031	0.025	0.0063
	[0.22]	[0.22]	[0.014]	[0.18]	[0.16]	[0.019]
Ruling Party Previous Election	0.52	0.57	-0.048	0.47	0.50	-0.031
	[0.50]	[0.50]	[0.033]	[0.50]	[0.50]	[0.056]
Observations	503	438		159	159	

TABLE 3

Effect of Electing Criminally Accused Politicians on the Growth of Night Lights

	(1)	(2)
Dependent Variable:	**Growth of Light**	
Panel A: Baseline		
Criminal	-26.67***	-17.31**
	[9.33]	[7.27]
State and Year Fixed Effects	No	No
R-squared		0.01
Panel B: State and Year Fixed Effects		
Criminal	-25.21***	-16.41**
	[8.46]	[6.58]
State and Year Fixed Effects	Yes	Yes
R-squared		0.13
Method	Local Linear Regression	Parametric
Observations	3,693	3,693

The dependent variable is *Growth of Light*. Criminal is a dummy variable that is 1 if a criminally accused candidate wins against a non-accused candidate and 0 if criminally accused candidate loses against a non-accused candidate. The RD estimates in column (1) are based on a local linear regression using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens-Kalyanaraman's (2012). The RD estimates in column (2) are based on a fourth-order polynomial in margin of victory and the interaction of the polynomial terms with the criminal dummy. In Panel B, we account for state and year fixed effects. In column (1), we do so by first regressing *Growth of Light* on state and year dummies and then using the residuals from this regression as the dependent variable. In column (2), we include state and year dummies in the regression equation. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4

Heterogeneous Effects of Criminally Accused: Local Linear Regression

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			**Growth of Light**		
Panel A: Local Linear Regression					
Criminal	-53.28***	-3.30	-30.57***	-4.78	-28.95
	[280.52]	[3.92]	[11.01]	[23.21]	[27.10]
State and Year Fixed Effects	No	No	No	No	No
Panel B: Local Linear Regression Using Residuals					
Criminal	-56.50***	-3.85	-29.52***	2.16	-11.73
	[19.04]	[3.69]	[9.92]	[21.32]	[23.47]
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	BIMAROU States	Non-BIMAROU States	Non-reserved Constituencies	SC Constituencies	ST Constituencies
Observations	1,309	2,384	3,065	441	183

The RD estimates above are based on a local linear regression using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens-Kalyanaraman's (2012). The dependent variable is *Growth of Light*. In Panel B, we account for state and year fixed effects by first regressing Growth of Light on state and year dummies and then using the residuals from this regression as the dependent variable. In column (1), the sample consists of BIMAROU states, which in our data is Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh and Uttarakhand. In column (2) we consider non-BIMAROU states. Columns (3), (4) and (5) restrict the sample to General constituencies, constituencies reserved for the Scheduled Caste (SC) candidates, and constituencies reserved for the Scheduled Tribes (ST) candidates respectively. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 5
Alternate Definitions of Criminally Accused: Local Linear Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			**Growth of Light**			
Panel A: Local Linear Regression						
Criminal	-24.23**	-15.43	-38.06**	-11.73	-34.17***	-48.84**
	[11.66]	[10.10]	[16.58]	[8.71]	[10.84]	[21.86]
State and Year Fixed Effects	No	No	No	No	No	No
Panel B: Local Linear Regression Using Residuals						
Criminal	-25.22**	-13.04	-40.93***	-8.42	-36.59***	-48.86**
	[10.97]	[8.93]	[14.44]	[7.77]	[10.41]	[19.98]
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Serious	Non-serious	Financial	Non-Financial	Multiple (>=2)	Multiple (>=5)
Observations	1,623	2,070	1,255	2,438	2,312	732

The RD estimates above are based on a local linear regression using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens-Kalyanaraman's (2012). The dependent variable is *Growth of Light*. In Panel B, we account for state and year fixed effects by first regressing Growth of Light on state and year dummies and then using the residuals from this regression as the dependent variable. In column (1), Criminal is 1 for a winner who had a serious criminal case against him and who ran against a non-criminal loser and 0 for a loser who had serious criminal accusation against him and ran against a non-criminal winner. In column (2), Criminal is 1 for a winner who had a non-serious criminal case against him and who ran against a loser who did not have any accusation and 0 for a loser who had a non-serious criminal accusation against him and ran against a winner who did not have any accusation against him. In column (3), Criminal is 1 for a winner who was involved in a financial crime and ran against a non-criminal loser and 0 for a loser who was involved in a financial crime and ran against a non-criminal winner. In column (4), Criminal is 1 for a winner who was involved in a non-financial crime and ran against a non-criminal loser and 0 for a loser who was involved in a non-financial crime and ran against a non-criminal winner. In column (5), Criminal is 1 for a candidate who had 2 or more criminal accusations and 0 otherwise. In column (6), Criminal is 1 for a candidate who 5 or more criminal accusations against him. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6

Effect of Electing Criminally Accused Politicians on the Growth of Night Lights: Sample Averages

	(1)	(2)
Dependent Variable:	**Average Growth of Light**	
Panel A: Baseline		
Criminal	-22.74***	-11.57**
	[8.46]	[5.64]
State Fixed Effects	No	No
R-squared		0.02
Panel B: State Fixed Effects		
Criminal	-18.88***	-11.60**
	[7.19]	[5.02]
State Fixed Effects	Yes	Yes
R-squared		0.23
Method	Local Linear Regression	Parametric
Observations	933	933

The sample considered is the average of the overall sample over the election term. The dependent variable is Average *Growth of Light*. Criminal is a dummy variable that is 1 if a criminally accused candidate wins against a non-accused candidate and 0 if criminally accused candidate loses against a non-accused candidate. The RD estimates in column (1) are based on a local linear regression using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens-Kalyanaraman's (2012). The RD estimates in column (2) are based on a fourth-order polynomial in margin of victory and the interaction of the polynomial terms with the criminal dummy. In Panel B, we account for state fixed effects. In column (1), we do so by first regressing *Growth of Light* on state dummies and then using the residuals from this regression as the dependent variable. In column (2), we include state dummies in the regression equation. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7

Alternate Definitions of Criminally Accused: Parametric Fit

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			**Growth of Light**			
Panel A: Parametric Fit						
Criminal	-16.81	-19.10*	-33.56**	-12.49	-25.26***	-51.88**
	[11.30]	[9.75]	[15.82]	[7.85]	[8.97]	[23.81]
State and Year Fixed Effects	No	No	No	No	No	No
R-squared	0.01	0.01	0.01	0.01	0.01	0.01
Panel B: Parametric Fit with Fixed Effects						
Criminal	-18.17*	-17.39*	-37.87**	-10.68	-25.62***	-50.53**
	[10.52]	[8.55]	[15.49]	[7.48]	[8.28]	[22.68]
R-squared	0.10	0.22	0.11	0.15	0.12	0.11
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Serious	Non-serious	Financial	Non-Financial	Multiple (>=2)	Multiple (>=5)
Observations	1,623	2,070	1,255	2,438	2.312	732

The dependent variable is *Growth of Light*. The RD estimates above are based on a fourth-order polynomial in margin of victory and the interaction of the polynomial terms with the Criminal dummy. In Panel B, we include state and year fixed effects in the regression equation. In column (1), Criminal is 1 for a winner who had a serious criminal case against him and who ran against a non-criminal loser and 0 for a loser who had serious criminal accusation against him and ran against a non-criminal winner. In column (2), Criminal is 1 for a winner who had a non-serious criminal case against him and who ran against a loser who did not have any accusation and 0 for a loser who had a non-serious criminal accusation against him and ran against a winner who did not have any accusation against him. In column (3), Criminal is 1 for a winner who was involved in a financial crime and ran against a non-criminal loser and 0 for a loser who was involved in a financial crime and ran against a non-criminal winner. In column (4), Criminal is 1 for a winner who was involved in a non-financial crime and ran against a non-criminal loser and 0 for a loser who was involved in a non-financial crime and ran against a non-criminal winner. In column (5), Criminal is 1 for a candidate who had 2 or more criminal accusations and 0 otherwise. In column (6), Criminal is 1 for a candidate who 5 or more criminal accusations against him. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8

Effect of Electing Criminally Accused Politicians on Constituency GDP Growth (in %)

	(1)	(2)	(3)	(4)	(5)
	Base	**Serious**	**Financial**	**Multiple (>=2)**	**Multiple (>=5)**
Coefficient	-25.2	-42.1	-76.4	-47.7	-60.1
Estimated Effect on GDP Growth (in %)					
Upper-Bound (Henderson et al., 2012)	-7.6	-12.6	-22.9	-14.3	-18.0
Lower-Bound (Bickenbach, 2014)	-2.7	-4.5	-8.2	-5.1	-6.4

The definition of the main explanatory variable changes across the columns: criminally accused. In column (1), in the base it takes a value of 1 for any candidate with at least one ongoing criminal accusation and 0 otherwise. In column (2), we consider only serious as defined by the Association for Democratic. In column (3), we consider only financial crimes. In column (4), we consider criminally accused who had 2 or more cases against them. In column (5), we consider criminally accused who had 5 or more cases against them. The upper-bound uses an elasticity of 0.3. The lower-bound uses an elasticity of 0.107.

TABLE 9

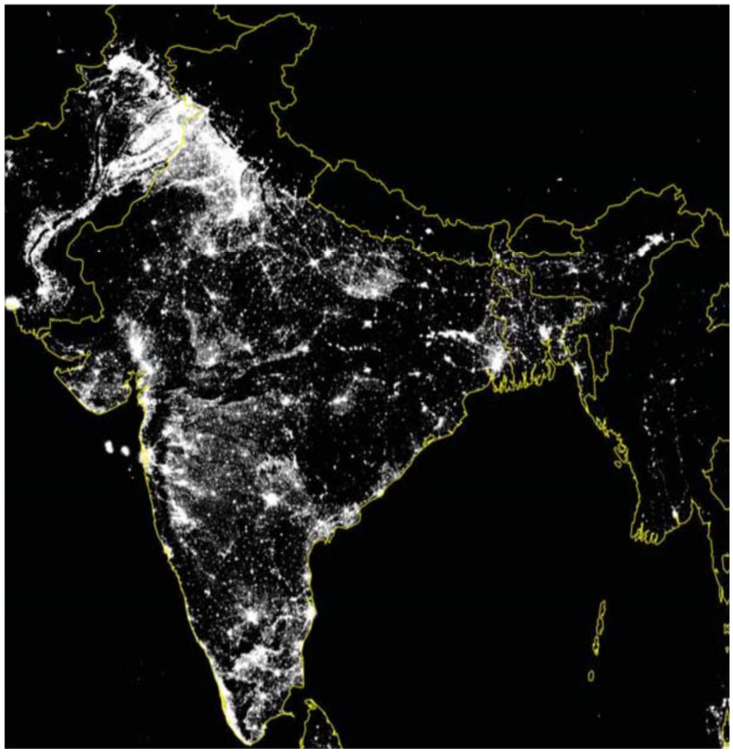
Heterogeneous Effects of Criminally Accused: Parametric Fit

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			**Growth of Light**		
Panel A: Parametric Fit					
Criminal	-40.69**	-4.32	-17.74**	-3.30	-43.39
	[16.46]	[4.04]	[7.96]	[29.28]	[28.87]
State and Year Fixed Effects	No	No	No	No	No
R-squared	0.01	0.01	0.01	0.01	0.03
Panel B: Parametric Fit with Fixed Effects					
Criminal	-42.37***	-4.48	-17.04**	-2.97	-39.65
	[15.01]	[3.99]	[7.08]	[31.41]	[26.26]
State and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.14	0.35	0.12	0.18	0.58
Sample	BIMAROU States	Non-BIMAROU States	Non-reserved Constituencies	SC Constituencies	ST Constituencies
Observations	1,309	2,384	3,065	441	183

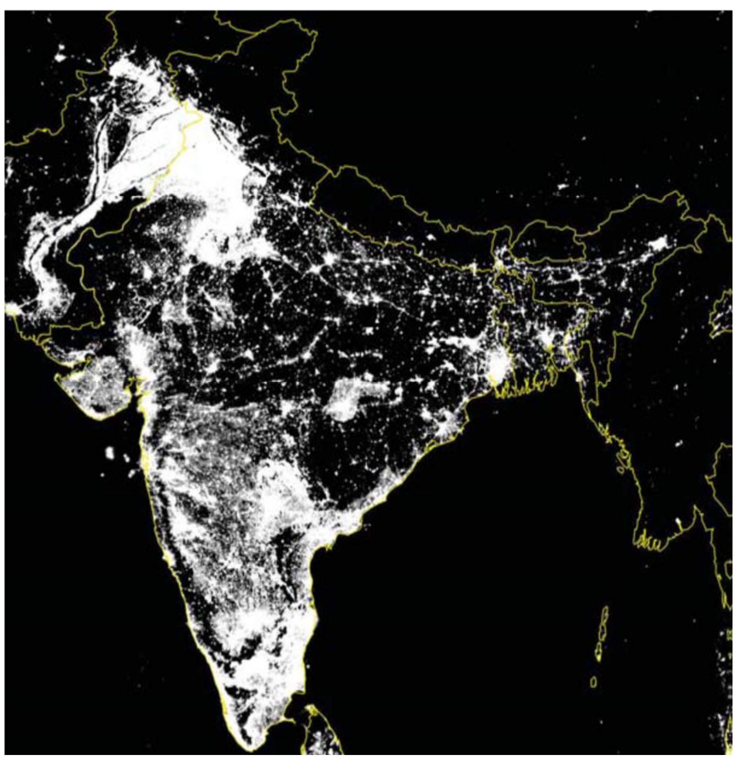
The dependent variable is *Growth of Light*. The RD estimates above are based on a fourth-order polynomial in margin of victory and the interaction of the polynomial terms with the Criminal dummy. In Panel B, we include state and year fixed effects in the regression equation. In column (1), the sample consists of BIMAROU states, which in our data is Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh and Uttarakhand. In column (2) we consider non-BIMAROU states. Columns (3), (4) and (5) restrict the sample to General constituencies, constituencies reserved for the Scheduled Caste (SC) candidates, and constituencies reserved for the Scheduled Tribes (ST) candidates respectively. Standard errors are clustered at the constituency level and given in parentheses.

The values with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1
Nighttime Light Output in India



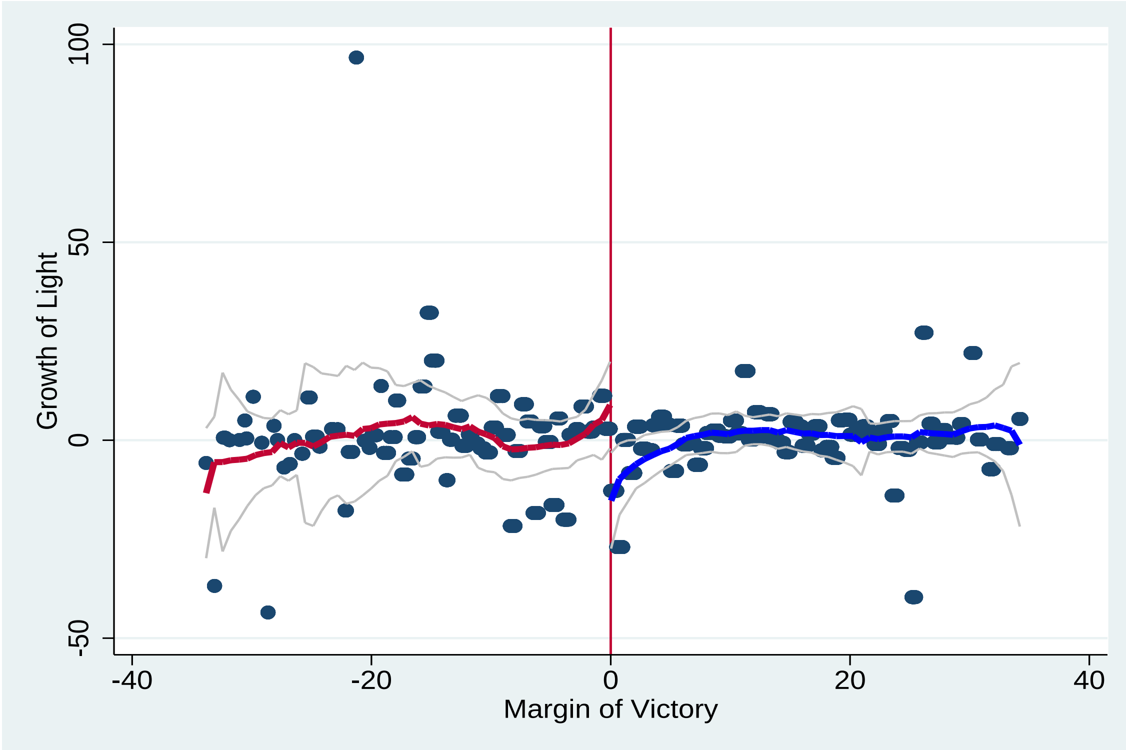
(a) 1992



(b) 2009

Figure 2

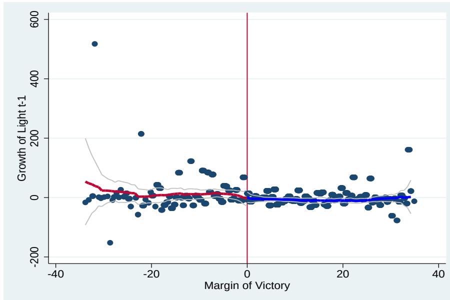
Effect of Criminal MLAs: All Criminals



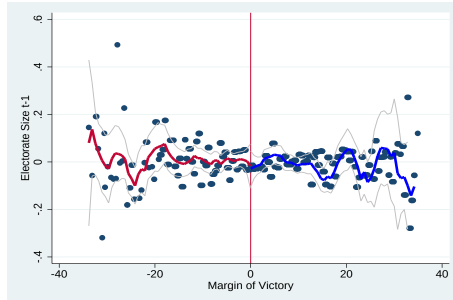
The running variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runnerup and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runnerup. The variable on the y-axis is the growth of light net of state and year fixed effects. The dots in the scatter plot depict the average of growth of light over each successive interval of 0.5% of margin of victory. The curves are local linear regressions fit separately for positive and negative margins of victory using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens and Kalayanaraman (2012). The confidence intervals are the 95% confidence intervals plotted using standard errors that are clustered at the constituency level.

Figure 3

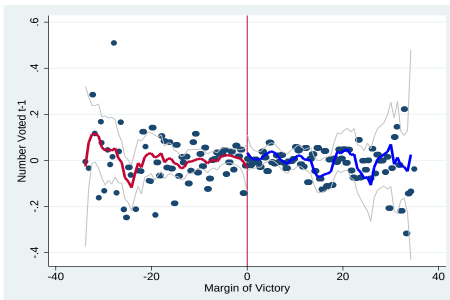
Predetermined Characteristics: Continuity Checks



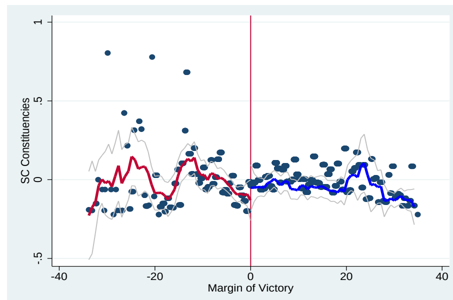
(a) Growth of Light t-1



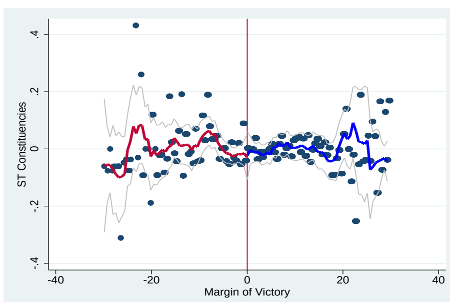
(b) Electorate Size t-1



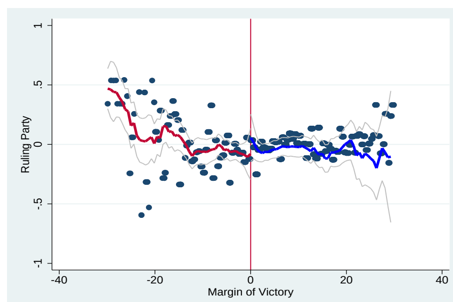
(c) Number Voted t-1



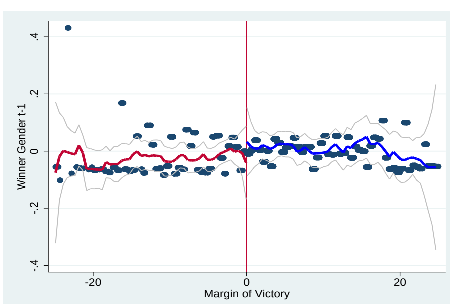
(d) SC Constituencies



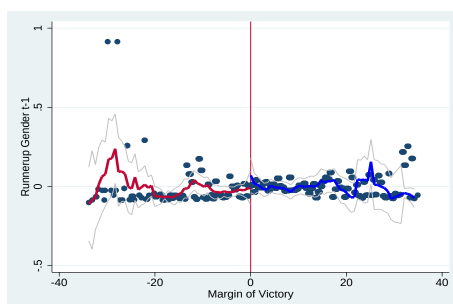
(e) ST Constituencies



(f) Ruling Party t-1



(g) Winner Gender t-1

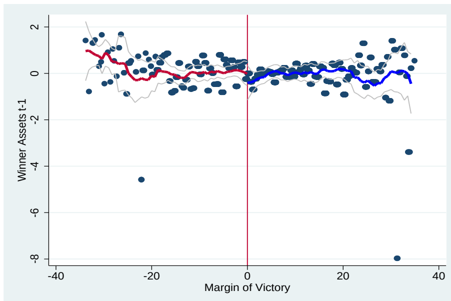


(h) Runner-up Gender t-1

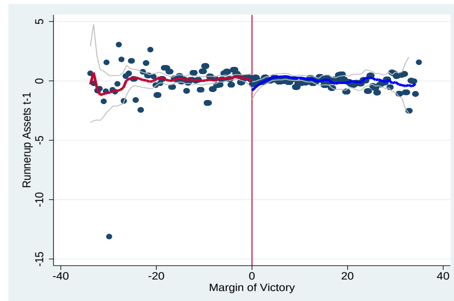
The running variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runnerup and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runnerup. Each variable on the y-axis is net of state and year fixed effects. The dots in the scatter plot depict the averages over each successive interval of 0.5% of margin of victory. The curves are local linear regressions fit separately for positive and negative margins of victory using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens and Kalayanaraman (2012). The confidence intervals are the 95% confidence intervals plotted using standard errors that are clustered at the constituency level.

Figure 3

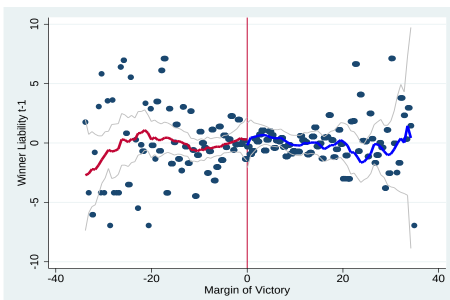
Predetermined Characteristics: Continuity Checks (contd)



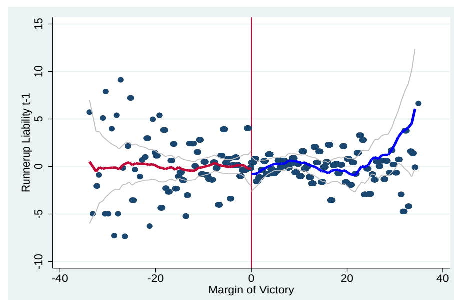
(i) Winner Assets t-1



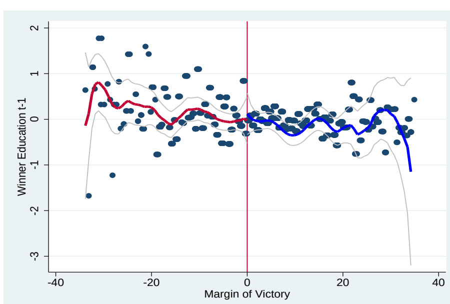
(j) Runner-up Assets t-1



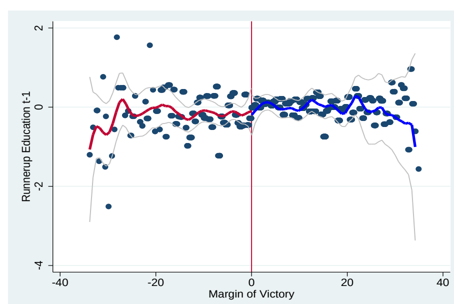
(k) Winner Liabilities t-1



(l) Runner-up Liabilities t-1



(m) Winner Education t-1

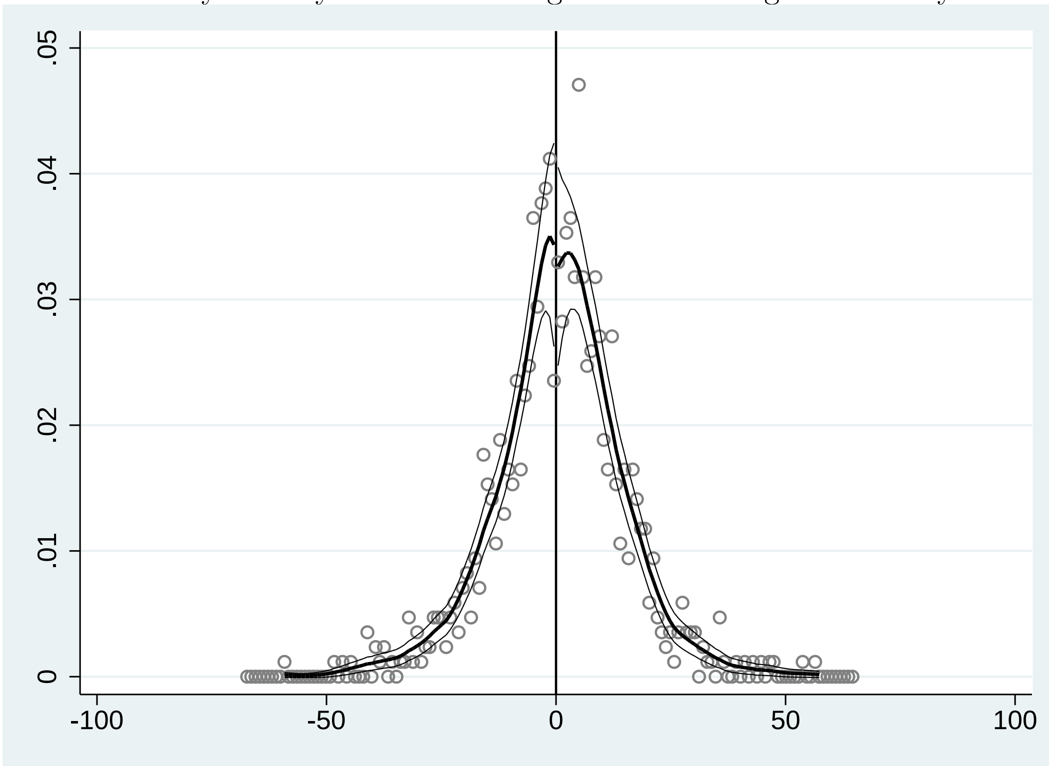


(n) Runner-up Education t-1

The running variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runnerup and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runnerup. Each variable on the y-axis is net of state and year fixed effects. The dots in the scatter plot depict the averages over each successive interval of 0.5% of margin of victory. The curves are local linear regressions fit separately for positive and negative margins of victory using a rectangular kernel and an optimal bandwidth calculator as suggested in Imbens and Kalayanaraman (2012). The confidence intervals are the 95% confidence intervals plotted using standard errors that are clustered at the constituency level.

Figure 4

McCrary Density Test of Running Variable: Margin of Victory



The running variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runnerup and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runnerup.
The estimated size of discontinuity in margin of victory (log difference in height) is -.061 (se=0.2).