Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India

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Abstract

We study the impact of electing criminally accused politicians to state legislative assemblies on constituency-level measure of economic activity in India. Using data on the criminal background of candidates running for state assembly elections and a constituency-level measure of economic activity proxied by intensity of night lights, we employ a regression discontinuity design that controls for unobserved heterogeneity across constituencies and find a 24-percentage points lower economic activity arising from the election of a criminally accused politician. These effects are driven by serious, financial and multiple criminal charges and are concentrated in less developed and more corrupt Indian states. Similar findings emerge for the provision of public goods using data on India's major rural roads construction program.

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"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)

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

1 Introduction

Despite the history of widely contested and transparent elections, and the presence of a vibrant and open media, India elects an ever increasing number of politicians facing criminal charges. This share has risen from 24 percent of members of the Indian Parliament in 2004 to 30 and 34 percent in 2009 and 2014 respectively (NY Times 2014).[1] While the election of criminally accused candidates to public office is concerning in any context, this is especially true in India. Large quantities of funds are distributed by the government through a wide variety of government interventions and programs, which have been plagued by costly scandals with losses in the hundreds of billions of dollars (Sukhtankar and Vaishnav 2015).[2] This problem is exacerbated by a severely understaffed judiciary and police force, thereby resulting in an extremely slow judicial system.[3,4] Taken together, this creates a context in which an influx of criminally accused politicians could be especially costly for an economy.

It is generally accepted, both in the literature and in public debate, that the election of criminally accused politicians has an adverse effect. Despite this widespread belief of an adverse effect, no formal estimates exist. In fact, it is quite possible that their election does not, on average, has a negative effect. Not only are some criminally charged candidates innocent, but criminal charges serve as a noisy signal of criminal behavior by candidates. For example, in the Indian context, political opponents have the incentive (and the means) to fabricate charges and criminal cases can also arise

[1] `http://india.blogs.nytimes.com/2014/05/23/in-the-newly-elected-indian-parliament-worrying-trends/?_r=0`.

[2] Looking at a statutory wage increase for participants in India's employment guarantee scheme (NREGS), Niehaus and Sukhtankar (2013) estimate a marginal leakage of 100%. Similarly, Baskaran et al. (2015), Nagavarapu and Sekhri (2013), and Min and Golden (2014) find that the allocation of electricity is distorted by political incentives.

[3] For instance, Suhkatankar and Vaishnav (2015) note that nearly 60 percent of police positions are unfilled in Uttar Pradesh. Nationwide, 20 to 30 percent of district, sub-ordinate and High court seats are unfilled.

[4] Close to a quarter of all cases have been pending for 5 years or more and there is a backlog of over 31 million cases (Suhkatankar and Vaishnav 2015).

from involvement by candidates in democratic protest movements (Jaffrelot and Verniers 2014). In this paper, we provide the first causal estimates of how the election of criminally accused politicians to state assemblies in India affects a measure of constituency-level economic activity.

An important challenge in this setting is to account for the unobserved heterogeneity between constituencies that elect criminally accused candidates and those that do not. For instance, criminally accused candidates may be more likely to run (and win) from certain constituencies than others. Therefore, constituencies that elect criminally accused candidates may not be comparable to constituencies that elect non-accused candidates. To isolate the causal impact of electing criminally accused candidates on a measure of economic activity, we use a regression discontinuity design (Lee 2008). This quasi-experimental design allows for a credible identification of the effect of electing criminally accused politicians by comparing constituencies in which an accused candidate barely wins with constituencies where a non-accused politician barely wins. The identifying assumption is that in close elections, the identity of the winning candidate (in this context whether the candidate is accused or not) is almost random (Lee 2008, Lee and Lemieux 2010).

We implement this empirical strategy by taking advantage of two important data sources for the time period 2004-2008, specifically data on criminal backgrounds of candidates running for public offices and data on the intensity of night lights. We rely on the data on criminal charges which became publicly available following a Supreme Court order in 2003 requiring all candidates seeking election to the Indian Parliament or State Legislative Assemblies to disclose their background information, including any currently open criminal charges.[5] This allows us to measure both the number and types of criminal accusations. Following recent studies (Henderson et al. 2012, Hodler and Rashky 2014, Storeygard 2014), we use satellite data on the intensity of night lights as a proxy for economic activity. While large household and economic surveys exist in India, these are only available at the district level and are not annual. The satellite data is available annually and can be measured at lower units including state assembly constituencies.

We find a strong negative effect on our constituency-level measure of economic activity. In our baseline specification, we observe a roughly 24-percentage point decline in the yearly growth of night

[5]As we subsequently describe, all candidates are required to file affidavits documenting any open criminal cases. Open criminal cases are more serious than a suspicion since this implies that there has been a formal investigation by police and that formal charges have been framed by a court. Consequently, this is synonymous with an indictment. Throughout the paper, we use the terms charges, accusation, and indictment interchangeably.

lights arising from the election of a criminally accused politician at the constituency level. This result is robust to alternate bandwidths and functional forms, and alternate measures of night lights intensity and its distribution across villages.

To better understand the underlying causes, we consider three dimensions. First, we consider the impact of different categories of charges and find substantial heterogeneity in their effects. In particular, the results are completely driven by politicians accused of serious and financial crimes (50 and 100 percent higher costs respectively than the effect in our baseline specification).[6] These costs further increase with the "intensity" of the treatment (i.e. the number of cases). In contrast, the election of politicians accused of only non-serious or only non-financial crimes have no statistically significant effect on economic activity. Second, we consider the accumulation of these costs over the state legislator's term in public office. When we consider year-to-year changes, we find that the negative impact is concentrated in the later years of the candidate's term in office. That is, the election of criminally accused politicians does not instantaneously result in lower economic activity. Third, we examine an alternate measure of economic development and a proxy for public good provision: the number of incomplete road projects in the constituency. This measure is likely to be uncorrelated with the supply or growth of electricity. In addition, it also highlights a plausible channel by which the election of accused politicians results in the lower growth of economic activity. The results are very similar to those using the intensity of night lights growth. In particular, the election of an accused politician increases the number of incomplete projects and the magnitudes increase for candidates accused of serious and financial crimes. Moreover, in constituencies in BIMAROU and high corruption states, the estimated effect almost triples.

Lastly, we examine spatial differences by focusing on the so-called BIMAROU states (which are generally considered to be less developed and highly corrupt)[7], levels of development (as defined by the Ministry of Finance, Government of India), and finally the levels of corruption (as defined by Transparency International India). Compared to our main result, the estimated coefficients for constituencies are approximately one and a half times larger for BIMAROU and the least developed states, and roughly two times higher for states with high levels of corruption.

As with any regression discontinuity, the estimates are only valid in the area surrounding the

[6] Financial charges are accusations related to a loss to the public exchequer.

[7] We use data for Bihar, Jharkhand, Odisha, Uttar Pradesh, and Uttarakhand. As is subsequently discussed, we do not have data for Madhya Pradesh, Chhattisgarh and Rajasthan which are also BIMAROU states.

discontinuity–in our case, in close elections won by accused politicians. The results do raise concerns about the broader influx of accused politicians into elected office. While several stories may be consistent with the results, in their totality, we believe that our results strongly indicate underlying criminal behavior by politicians, and, crucially, the importance of the institutional context.

This paper makes contributions to several related literatures. Most narrowly, it contributes to an emerging literature on criminally accused politicians in India. While the existing studies typically focus on the selection of these candidates, some examine the response of voters to information on criminal status or criminal charges and the potential mitigating effect of caste politics (Banerjee et al. 2014, Charchard 2014). Others examine the selection of these candidates by political parties (Aidt et al. 2012, Tiwari 2014, Vaishnav 2011, 2011a, 2011b).[8] These studies implicitly (and sometimes explicitly) assume that the election of criminally accused politicians is not desirable. Surprisingly, this is unknown. Our study provides the first evidence of whether there is an economic cost to the election of the criminally accused politicians at the constituency level (from which they are elected and represent).

More broadly, we build on the literature on politicians' effects on sub-national (and local) economic activity and efficiency. These studies have mostly examined the role of election cycles on public expenditure and service delivery (Akhemdov and Zhuravskaya 2004, Bhaskaran et al. 2015, Ferraz 2007, Khemani 2004, Schady 2000), the relationship between politics, connections and the provision of loans (Cole 2009, Dinc 2005, Fisman 2001, Kwaja and Mian 2005), and the influence of politicians on outcomes via their influence on bureaucrats (Iyer and Mani 2012, Nath 2014, Wade 1982). Despite anecdotal evidence of potentially criminal activity by politicians, we are unaware of any papers that directly focus on estimating the impact of electing criminally accused politicians on economic activity measured at the constituency level.

Similarly, the literature regarding the quality of politicians typically uses proxies such as education (Alcantara 2008, Besley et al. 2005, De Paola and Scoppa 2010, Martinez-Bravo 2014) and, more recently, personality (Callen et al. 2015). As our results demonstrate, whether or not a politician is criminally accused may have an important effect on the constituency level outcomes. Consequently, we believe that this may represent a novel pre-election indicator of politician quality. Since criminally

[8] We are agnostic on the reasons for why accused politicians are selected by political parties and elected by voters. Rather, we note the trend and ask what the local economic consequences are.

accused politicians are not limited to India, this indicator can be applied more broadly. Finally, although our study focuses on India, it contributes to our broader understanding of the costs of electing lower quality politicians in developing countries.

The remainder of this paper is organized as follows. In Section 2 we provide the background on the elected representatives in India and discuss the corruption and criminality in Indian politics. Section 3 discusses the empirical strategy, followed by the data description and the validity of the regression discontinuity design in Section 4. We present the main results, robustness checks, discussion of underlying causes, and heterogeneous impact by state characteristics in Section 5. We estimate the economic costs by doing a back of the envelop calculation in Section 6. We provide our conclusions in Section 7.

2 Background

2.1 Elected Representatives in India

India is a federal republic with a parliamentary system of government, where the political structure of the states parallels that of the national structure. The Parliament of India consists of two Houses–an Upper House (also called the Rajya Sabha or Council of States) and a 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). States in India follow a similar structure where the Upper House is called the Legislative Council (or Vidhan Parishad) and the Lower House is called the Legislative Assembly (or Vidhan Sabha). Those elected to the state Legislative Assembly are referred to as Members of the Legislative Assembly (or MLAs). Similar to the national level, the election system at the state level is a "first-past-the-post" system and constituencies are divided into a single member constituencies. The focus in this paper is on the members elected to the state Legislative Assemblies (MLAs). The term of each MLA is 5 years, although it is possible to have elections before the 5-year term mostly due to shifting of political alignments.

The Indian Constitution grants elected representatives enormous responsibilities. In particular, MLAs hold legislative, financial, and executive power. In addition to the constitutional powers, they also have control over the state bureaucracy (for e.g. in promotions, and job assignment/transfers) (Asher and Novosad 2015, Iyer and Mani 2012, Krishnan and Somanathan 2013, Nath 2014, Sukhtankar and Vaishnav 2015).[9] Bureaucrats are particularly important as they play a key role in the allocation of funds for various development projects, the distribution of licenses, facilitate access to governmental schemes. Collaboration with or control of the bureaucracy also allows politicians to act as the mediators between the private sector and the government, and lobby political allies and business contacts to bring projects to their constituencies (Bussell 2012, Chopra 1996, Jensenius 2013). Finally, MLAs also have access to discretionary development funds, also known as the Member of Legislative Assembly Constituency Development Scheme, which they can spend on development projects within their constituencies. Therefore, elected representatives can directly and indirectly affect economic activity in their constituencies.

2.2 Corruption and Criminality in Indian Politics

It is widely believed that there is a criminal nexus between politicians and criminals. Elected officials are also widely reputed to be involved in corruption, mostly graft and embezzlement of public funds (BBC News India 2012, India Today 2012). A recent paper by Sukhtankar and Vaishnav (2015) compiled an inventory of the biggest public corruption scandals uncovered after 2003, and found amounts totaling in the hundreds of billions of dollars.[10] Fisman et al. (2014) utilize the asset disclosures of candidates for Indian state legislators and compare 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. They find that the estimated annual growth rate of winners' assets is 3-5 percent higher than that of runners-up. Similarly, Bhavnani (2012) compares the change in winners' and losers' self-declared family assets in India's two most recent state and national elections, and finds that the average election winner increased his assets by 4-6 percent a year.[11]

[9]The nexus between politicians and bureaucrats, and in particular, the bribe involved in the job assignment/transfer of bureaucrats was recently admitted in a press conference on May 22, 2015 by an incumbent Chief Minister of Delhi (http://www.ndtv.com/video/player/news/kejriwal-says-centre-has-betrayed-people-of-delhi-by-siding-with-lieutenant-governor/368367).

[10]Table 1 of Sukhtankar and Vaishnav (2015) estimates the mean scam "value" was Rs. 36,000 crore (about 5.6 billion USD), and the median was Rs. 12,000 crore (about 1.9 billion USD).

[11]According to Banerjee et al. 2011, 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 average annual salary of MLAs in Uttar Pradesh is approximately $12,000. The political affiliation was especially important as MLAs who belonged to the political party heading the state government (or the

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 judgement of the Supreme Court of India in 2003. In 2003, the Supreme Court of India required candidates seeking election to the Parliament or a Legislative Assembly to file sworn affidavits containing information on their professional and educational qualifications, their assets and liabilities and those of their immediate family, as well as the information regarding criminal convictions and charges. In particular, the affidavits require candidates to report prior convictions and any open accusations for which the offence is punishable with imprisonment for two years or more, and in which charge is framed or cognizance is taken by the Court of Law (that is, any criminal indictment). These charges are limited to those framed in the 6 months preceding the election. Since candidates face penalties for lying on the sworn affidavits and rival candidates (and the media) have incentives to verify this, deliberate misreporting should be minimized.[12] [13]

The Association for Democratic Reforms (ADR), an election watchdog, along with the National Election Watch have conducted so-called Election Watches for all state and federal elections since 2003 in India.[14] The surprising finding is that the percentage of MPs facing criminal charges has increased between the 2009 and 2014 Lok Sabha elections.[15] The findings are similar for the state assembly elections. According to the ADR report, over 30 percent of the MLAs currently face criminal cases in India.[16]

ruling party) saw their asset value increase by an average of $500,000. For opposition party members, this increase amounted to less than $300,000.

[12]These are sworn affidavits and there is a penalty for filing incorrect affidavit (for e.g. disqualification, imprisonment for a term which may extend to six months, or with fine, or both).

[13]The affidavits can be accessed from the ECI's website (`http://eci.nic.in/eci/eci.html`) and its website on candidate affidavit (`http://eci.nic.in/eci_main1/LinktoAffidavits.aspx`).

[14]Election Watch comprises of 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.

[15]This percentage increased from 30 percent in 2009 to 34 percent the recently concluded 2014 election.

[16]For example, in one of most populous and politically important state, Uttar Pradesh, 575 of the candidates for the 403 assembly seats had criminal backgrounds or faced criminal charges during the 2007 state legislative assembly elections. Out of these, 140 won the assembly seats. Following this success, it is not surprising that an even greater number of criminally accused candidates (759) ran in the next elections in 2012. Of these, 189 won seats in the state assembly (ADR, 2012a).

3 Regression Discontinuity Design

A key contribution of this paper is the identification of the causal effect of electing criminally accused politicians to state assemblies in India on local economic activity. The main challenge in estimating the effect of electing criminally accused candidates on economic activity is that the victory of criminally accused politicians is not random; for example, criminally accused candidates may be more likely to run and win from certain constituencies than others in ways that are unobservable to us. As a result, average differences in economic activity between constituencies that elected an accused MLA and those that elected a non-accused MLA will result in a biased estimate of the effect of electing criminally accused candidates.

A Regression Discontinuity (RD) design (Lee 2008, Imbens and Lemieux 2008) allows us to exploit a discontinuity in the treatment assignment to identify the causal effect of a treatment variable.[17] In our setting, the assignment of treatment, whether a candidate is criminally accused or not ($CRIMINALLY\ ACCUSED$), is determined solely on the basis of a cutoff value, c=0, of the forcing variable, the victory margin ($MARGIN$). The treatment assignment follows a known deterministic rule, $CRIMINALLY\ ACCUSED = 1\ (MARGIN \geq c)$, where $1\ (.)$ is the indicator function. The constituencies which fall below the cutoff ($MARGIN < 0$), the control group ($CRIMINALLY\ ACCUSED = 0$), elect a non-accused candidate who won against an accused runner-up, and victory margin in these elections is the difference in the vote shares of the accused runner-up and the non-accused winner. Constituencies that fall above the cutoff ($MARGIN \geq 0$), the treatment group ($CRIMINALLY\ ACCUSED = 1$), elect a criminally accused candidate who won against a non-accused runner-up, and the victory margin in these elections is the difference in vote shares of the accused winner and the non-accused runner-up. Therefore, at the victory margin of zero, the accusation status of a politician changes discontinuously from non-accused to criminally accused. Thus, as the victory margin becomes arbitrarily small i.e. as we move closer to the cutoff, the outcome of an election is as good as random. As a result, constituencies that barely elected a non-accused politician in a close election serve as a valid counterfactual for constituencies that barely elect a criminally accused politician.

[17] The seminal paper by Lee (2008) exploits a regression discontinuity design using electoral data. Studies using similar design in the context of India and elsewhere include Asher and Novosad (2014), Bhalotra et al. (2013), Bhalotra and Clots-Figueras (2014), Broockman (2014), Clots-Figueras (2011, 2012), Fisman et al. (2014), and Uppal (2009).

We consider the following specification for estimating the RD treatment effect of electing a criminally accused candidate to state legislative assemblies relative to a non-accused candidate:

$$Y_{i,s,t+1} = \alpha_s + \beta_{t+1} + \gamma CRIMINALLY\ ACCUSED_{i,s,t} + f(MARGIN_{i,s,t}) + e_{i,s,t+1} \quad (1)$$

$\forall\ MARGIN_{i,s,t} \in (c-h,\ c+h)$

where $Y_{i,s,t+1}$ is the outcome of interest, i.e. yearly growth in night lights $[Log(Y_{i,s,t+1})$-$Log(Y_{i,s,t})]$.[18] α_s is the state fixed effects and control for any time-invariant state characteristics. β_{t+1} is the time fixed effects and control for any macroeconomic shocks or national policies that affected all states uniformly, and for changes in satellite technology over time. The variable $CRIMINALLY\ ACCUSED_{i,s,t}$ is the treatment, $MARGIN_{i,s,t}$ is the forcing variable, and h is the neighborhood around the cutoff c=0, also referred to as the bandwidth. The control function $f(MARGIN_{i,s,t})$ is some continuous function, usually a n-order polynomial in the forcing variable on each side of c.[19] Finally $e_{i,s,t+1}$ is the error term. The coefficient of primary interest is γ, which estimates the causal impact of electing criminally accused politicians to state assemblies in India on economic activity as proxied by the growth of night lights.

In this paper we estimate a local linear regression (Hahn, Todd, and Van der Klaauw 2001, Porter 2003, Imbens and Lemieux 2008) as it allows for a suitable bandwidth with a linear control function. We follow the algorithm proposed by Imbens and Kalyanaraman (2012) to calculate an optimal bandwidth (referred to as h) for each regression. In addition, as a robustness check, we also estimate the local linear regression using the optimal bandwidth proposed by Calonico, Cattaneo and Titiunik (2014), half the optimal bandwidth (h/2), and twice the optimal bandwidth (2h). Since growth in night lights is likely to be correlated over time within a constituency, the standard errors are clustered at the constituency level.

[18] We omit the year of the election as it might be capturing the impact of the previous candidate.

[19] Different variations of equation (1) with different bandwidths and control function have been used in the literature. For example. Lee, Moretti and Butler (2004) use parametric regression-based higher order polynomials in the control function (second-order, third-order, and fourth-order polynomials), thus allowing all the observations to be used in the RD estimation. However, this method puts equal weight on observations far from the cutoff, which can be misleading (Gelman and Imbens 2014).

4 Data Description and Validity of the RD Design

4.1 Night Lights as a Measure of Economic Activity

To reliably examine the costs associated with electing criminally accused candidates, we need measures of economic activity at the State Assembly constituency level, our unit of analysis. To the best of our knowledge, no such data exist in India. Large surveys, such as the National Sample Survey, India Human Development Survey and Economic Census of Firms, are only available at the district level. In theory, it is possible to make use of the above mentioned data sets, however, on average, there are approximately 6 to 7 constituencies per district. Since the number of constituencies varies across districts and there is no logical way to weight constituencies within districts, the district level data cannot be easily matched to various constituencies. [20] Moreover, even if a measure of state constituency level economic activity could be derived, the above mentioned surveys are not available annually.

We use data on the intensity of night lights that proxies for economic activity. Although the intensity of night lights is not a perfect measure of economic activity, Henderson et al. (2012), Hodler and Rashky (2014), and Storeygard (2014) find a strong relationship between GDP and night light intensity at the sub-national level using a cross-section of countries and in the Sub-Saharan Africa.[21,22] In addition, Bickenbach et al. (2013) validates the use of the night light intensity for India using district level measure of GDP. Despite some drawbacks, these data have several advantages as each pixel can easily be aggregated to the constituency level and the availability of annual frequency allows for more detailed temporal analysis. However, whether through increased electrification or higher incomes levels, it should arguably be related to local economic activity.

[20] Based on the Delimitation Order of 1976, the constituency boundaries remained fixed till 2008. As a result, there were 4,120 state assembly constituencies. According to the Delimitation Order of 2008, the number of Assembly constituencies are 4,033. There were 593 districts in India according to the 2001 Census, while according to the 2011 Census, there are 640 districts.

[21] Henderson at al. (2012) show that night lights can also pick short run fluctuations, including the Asian Financial Crisis in Indonesia between 1997 and 1998 and the Rwandan Genocide between 1993 and 1994. Thus satellite night lights data are a useful proxy for economic activity at temporal and geographic scales for which traditional data are of poor quality or are unavailable (Henderson et al. (2012). Additionally, prior research shows that Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) can reliably detect electrified villages in developing countries and that night lights output is a useful proxy for electricity provision (Doll et al. 2006; Min et al. 2013; Baskaran et al. forthcoming).

[22] Recent papers have used night lights data to study growth of cities in sub-Saharan Africa (Storeygard 2014), production activity in blockaded Palestinian towns of the West Bank (Abrahams 2015), van der Weide et. al (2015), and urban form in China (Baum-Snow and Turner 2012) and India (Harari 2015).

The satellite data originally come from the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), which uses a set of military weather satellites that have been orbiting the earth since 1970. The satellites record high resolution images of the entire earth each night typically between 8:30 and 10:00 pm local time. The 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 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, and removing ephemeral lights like fires, other temporary lighting phenomenon and noise.

The result is a series of images covering the globe for each year from 1992 onwards (Elvidge et al. 1997, 2001). Images are scaled onto a geo-referenced 30 arc-second grid (approximately 1 km^2). Each pixel is encoded with a measure of its annual average brightness on a 6-bit scale from 0 to 63. Thus, it is top-coded at 63 and censored at 0, i.e. the brightest areas are not well measured and areas require some minimum level of light to be captured. In our baseline RD sample, there are 63 fully lit constituencies. The top-coding is a concern since we are unable to observe increases in lighting above 63. However, this should not be systematically related to close elections of criminally accused candidates. That said, we subsequently replicate our analysis with and without the top coded constituencies to verify the robustness. Another potential issue is blooming, which occurs when light from a brightly lit area appears to spill out into neighboring areas. While this is a concern around large cities, our sample is predominately rural. Lastly, the levels of light output are relative brightness values. There is no onboard radiance calibration on the satellite sensors, thus there is no way to convert the relative brightness values to an actual level of illumination. This complicates time series analysis because changes in observed brightness in different annual composites may be due to real changes in light output on the ground or due to technical factors related to gain levels and sensor properties. We follow Henderson et al. (2012) and Chen and Nordhaus (2011), and account for this limitation by including year fixed effects in our estimating equation to control for contemporaneous shocks affecting all units in a year, including any factors that may affect the overall brightness detected by a sensor in any given year. Finally, we utilize the data available on stable night lights that drop light values from pixels with unstable light signatures over time.

Our primary dependent variable is the annual growth in night lights. This is the difference in the natural log of night lights intensity for the constituency between the current (t) and the previous period (t-1). As discussed earlier, this has been widely accepted in the literature as a proxy for economic activity. Another advantage of specifying the dependent variable in this form (i.e. the difference in natural logs) is that it provides a rough estimate of the impact on GDP using estimates of the elasticity of GDP growth to night light growth from the literature. In addition, we also show results using three alternate dependent variables, the natural log of night lights, the proportion of lit villages within a constituency, and growth of night lights averaged over the entire election term.[23] These additional dependent variables are likely to be less sensitive when comparing growth of night lights over time. We report the descriptive statistics of the key dependent variables in Table 1-A.

Finally, when we explore a potential channel, we use a non-satellite measure of public good provision at the constituency level: the number and share of incomplete roads projects. In particular, we use the official data from Pradhan Mantri Gram Sadak Yojana (PMGSY) that was launched in December 2000. PMGSY is a fully funded centrally sponsored scheme that aims to provide all weather road connectivity in rural areas in India. We match the roads data to the state assembly constituency level data for the empirical analysis. [24]

4.2 Election Results and Affidavit Data

We use the Election Commission of India (ECI) Statistical Reports on General Elections to State Legislative Assemblies[25] for election data. These reports provide all the information related to an election, such as the name and code of the constituency, candidates and their vote shares, electorate size (number of registered voters), number of voters, turnout, gender and constituency type (reserved or non-reserved constituencies).[26] For criminal accusations, we rely on the data from affidavits that

[23]The proportion of lit villages within each constituency is the number of villages with detectable stable light output observed at the village center divided by the total number of villages, which is the proportion of villages with positive light output within each constituency. A typical constituency had a total light output of 1,956 "brightness" units in 1992, and this increased to 3,745 by 2008. The proportion of lit villages was just under half in 1992 but increased to 69-percent by 2008 [Baskaran et al. (forthcoming)].

[24]The PMGSY data is available at the census block level. There is no one-to-one matching between census blocks and Assembly constituencies. For example, a block can span more than one constituency. We however match a block to a specific constituency if at least 50 percent of the villages in the block fell in that constituency.

[25]`http://eci.nic.in/eci_main1/ElectionStatistics.aspx`, accessed in May 2014.

[26]According to the Indian Constitution, certain seats are reserved for Scheduled Castes (SCs) and Scheduled Tribes (STs), the two historically disadvantaged minority groups. While registered voters from all social groups can vote, only an SC (ST) candidate may contest election from the seats reserved for SC (ST).

have been collected and digitalized by the Election Watch, in collaboration with the Association for Democratic Reforms (ADR).[27] The ADR data provides information on the number of criminal cases against each candidate, the charges associated with each criminal case, classification of a crime as serious or not, asset and liabilities of each candidate and each candidate's level of education. We consider all state elections held between 2004 and 2008.

While the light data is available from 1992 onwards, we are limited by data on affidavits, which were made mandatory only after the Supreme Court order in 2003. Further, ADR data is available only for elections held after 2004. As a result, we have a sample of 20 states out of a total of 28 covering approximately 90 percent of India's total electorate.[28] The constituency boundaries changed in 2008 meaning constituencies before and after delimitation are not comparable.[29] Thus, between the Court order to file affidavits in 2003 and redrawing of boundaries in 2008, we observe only 1 election per state. However, we utilize the light data until 2012 for some states.[30] Appendix Table A-1 reports the information on the number of assembly constituencies and information on year in which the elections were held in each state after the Supreme Court order from the ADR website.

Our main variable of interest is criminal accusations.[31] A potential concern with accusations is that political rivals may file false cases to gain electoral advantages. Unfortunately, it is not possible to distinguish between "true" and "false" criminal accusations. Despite this limitation, these data

[27]The ADR data is available for public use at `www.myneta.info`.

[28]The included states are Arunachal Pradesh, Assam, Bihar, Goa, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Kerala, Maharashtra, Manipur, Meghalaya, Nagaland, Odisha, Punjab, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand and West Bengal. The states excluded from our analysis are Andhra Pradesh, Chhattisgarh, Jammu and Kashmir, Karnataka, Madhya Pradesh, Mizoram, Rajasthan and Sikkim. Note that these states are excluded from the analysis based on the pre-determined timing of their elections. Consequently, there is no reason to believe that there are any systematic differences between included and excluded states (particularly with respect to growth of night lights or criminally accused candidates).

[29]The boundaries for constituencies were fixed in 1976 until 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 a comparison between the two periods.

[30]The affidavits are available starting first election held after the Supreme Court order in 2003. For example, the order was first effective in 2004 in Arunachal Pradesh and the first election after the boundaries changed was held in 2009. So for Arunachal Pradesh, our (post-treatment) sample period is from 2004-2009. However, for Uttar Pradesh the first election after the order, took place in 2007 and the first election after the changes in the boundaries was held in 2012. As a result, our sample period for Uttar Pradesh is from 2007-2012.

[31]It is not possible to examine convictions since there are only a handful of cases in which criminal proceedings lead to a convinction. Ideally, we would be able to use earlier accusations and examine whether candidates are subsequently convicted. However, the data on accusations is only recent and the Indian judicial process frequently takes years or even decades to resolve cases. According to Sukhtankar and Viashnav (2015), of the 76 MPs serving in the 15th Lok Sabha (2009 national elections) who faced ongoing criminal action, the case had been pending for an average 7 years.

have been widely used to measure criminal accusations (Aidt et al. 2015, Asher and Novosad 2014, Banerjee et al. 2014, Fisman et al. 2014). There is evidence to suggest that false cases are not as frequent as might be believed. Looking at a sub-sample of states, Vaishnav (2011) finds that accusations are unrelated to prior electoral performance (a proxy for popularity), incumbency, and the timing of elections. In addition, only cases filed 6 months prior to elections need to be reported, therefore it is less likely the criminal charges are electorally motivated.

In our baseline specification, we define a binary variable for whether or not a candidate is currently accused in any criminal case. Specifically, this variable takes a value of 1 if MLA faces any current criminal cases and 0 otherwise. Given the setup in a RD design, we only consider races in which, among the top-2 candidates, one is accused and the other is non-accused. This is because the RD design implicitly assumes that voters are faced with a choice between two types of candidates (accused and non-accused). In practice, the top 2 (or even all the candidates) might be of the same type. We therefore restrict the sample to constituencies in which the top two candidates represent each type. This restricts our sample from the full 2633 constituencies for which we have data to a smaller sample of 941 constituencies, which are observed annually during our sample period in between elections totaling over 3600 observations.[32]

While we are not the first study to use the data on criminal accusations, only a few studies, Vaishnav (2011) being a notable exception, consider the type of charges. This is particularly important since not all charges are of the same severity or relevance in assessing a candidate's aptness for public office. We consider whether a specific charge associated with a criminal case is serious or not, and whether it is related to any financial wrongdoing or not. Since any definition of a serious criminal charge is inherently arbitrary, we rely on a classification used by the ADR, such as the maximum punishment under the law, their violent nature, and offenses under the Prevention of Corruption Act.[33] Since ADR does not classify charges into financial and non-financial categories,

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

[33]ADR compiles the detailed data on each candidate's criminal cases and the type of charges farmed in each case. Thus it reports the exact criminal charge(s) for each candidate as defined under the Indian Penal Code (IPC). IPC is the main criminal code of India that covers all substantive aspects of criminal law. ADR defines serious criminal charges using eight criteria. They are: (1) Whether the maximum punishment for the offence committed is of five years or more, or; (2) Whether the offence is non-bailable, or; (3) Offences pertaining to the electoral violation (IPC 171E or bribery), or; (4) Offence related to the loss to exchequer, or; (5) Offences the nature of which are related to assault, murder, kidnap, rape, or; (6) Offences that are mentioned in Representation of the People Act, or; (7) Offences under Prevention of Corruption Act, or; (8) Offences related to the Crimes against women. The following is a link to an online Appendix on ADR criteria for coding serious crimes:`http://adrindia.org/content/`

we define a charge as financial if the corresponding IPC refers to a crime resulting in a loss to public exchequer.[34] Similar to the variable for any criminal case, we create binary variables for whether or not a candidate is accused of a serious or financial criminal charge.

Our baseline definition of criminal accusations is whether a candidate has any criminal case against him/her. We refine our definition of criminally accused further by considering candidates who face multiple criminal cases. Insofar as there is a cost to framing false cases against politicians, we might expect that a higher number of cases might be a more reliable indicator of a politician's true type. Additionally, this also provides a measure of the "intensity of the treatment". Accordingly, we should expect the treatment effects to become larger as the treatment intensity increases. We consider two thresholds: a candidate is criminally accused if he/she has 2 or more cases or if he/she has 5 or more cases. We define similar thresholds for serious and financial crime. However, we make a distinction between the number of charges and cases. A criminal case may have multiple charges associated with it.[35]

Table 1-C reports descriptive statistics of the data on criminal accusations. Approximately 54-percent of the winners in our sample report at least one criminal case, while 40-percent are facing at least one serious charge, and 20-percent at least one financial charge. Although some of the differences between the winners and the runners-up are statistically significant in the full sample in Table 1-B, these become insignificant when we look at close elections in our sample. Further, Appendix Figure A-4 depicts the distribution of criminally accused MLAs across Indian States.

4.3 Validity of the RD Design

There are two standard tests to show the validity of the RD design (Imbens and Lemieux 2008). The first is the McCrary (2008) density test for a jump around the cutoff in the density of the forcing

`criteria-categorization-serious-criminal-cases.`

[34]This classification is based on consultations with several high level Indian police officers and we labels the following IPCs as financial crimes: 171B, 171E, 230–262, 272, 273, 274, 275, 276, 378–420, and 466–489D.

[35]It is important to emphasize why we distinguish between charges and cases while considering serious and financial criminal accusations. Suppose a candidate reports two serious criminal cases in his/her affidavit. In the first case, this candidate is accused of murder and robbery while in the second case, he/she is accused of murder, kidnapping and rape. Therefore, when we consider the number of serious cases, this will be counted as two; when we consider number of serious criminal charges, this will be counted as five. To make our point clearer, within the same criminal case, a candidate cannot be charged with same crime twice according to the IPC. For example, suppose in the first case the candidate murdered five people, therefore he/she will only be accused of one murder charge and not five. However, for completeness, we repeat the exercise by using both number of cases and charges, keeping the same thresholds.

variable. In our context, this tests for whether criminally accused candidates disproportionately win close elections. For instance, criminally accused politicians might be able to manipulate elections and therefore more likely to win close elections, thereby violating the identifying assumption that treatment is randomly assigned. If this were the case, we would find a larger frequency of criminally accused candidates in the neighborhood of the cutoff compared to non-accused candidates. This would imply that the density of the margin of victory, the forcing variable, would show a discontinuity at the cutoff. Figure 1 shows that the desntiy of the victory margin above and below the cutoff is not statistically significant. In fact, the density above the cutoff (while insignificant) is actually lower than that below.

The second test of the validity of the RD design is whether the observed characteristics of candidates and constituencies are continuous around the cutoff. That is, while the characteristics for criminally accused and non-accused candidates may be different over the entire sample, with the exception of the treatment, no other variable should jump around the cutoff. For instance, recent papers (Caughey and Sekhon 2011, Grimmer et al. 2011) have shown that in the context of U.S. elections, the incumbent party tends to have systematically greater chances of winning even when elections are close. However, Eggers et al. (2014) use data on 40,000 closely contested races in different electoral settings, including India, and do not find any systematic evidence of sorting or imbalance around the electoral thresholds.

We formally check for continuity of various constituency and candidate characteristics in Figure 2. The 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 triangular 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.

In Panels (a)-(p), we compare accused winners to non-accused winners on growth of night lights in the prior year (t-1 and t-2) and on several other constituency and candidate characteristics: constituency characteristics are electorate size, number of voters, whether a constituency was aligned with the ruling party in the state, in the previous election, and whether a constituency is reserved for Scheduled Caste (SC) or Scheduled Tribes (ST); while the candidate characteristics are MLA's gender, education, asset, liabilities, and incumbency status. The results indicate that there are no statistically significant differences in the observed covariates around the cutoff. Therefore results from the McCrary test and the continuity of covariates strongly suggest that the assumptions underlying the RD design are valid in this setting and that the outcomes of a close election is as good as random.

5 Criminally Accused Politicians and Economic Activity

5.1 Main Results

We present the main results with the graphical illustration of the RD effect of electing criminally accused candidates in Figure 3 which plots the yearly growth of night lights against the margin of victory for the criminally accused candidates. The yearly growth of night lights is the residual from the regression of yearly growth of night lights on state and year dummies. The scatter plot contains the local averages of the residuals in each successive interval of 0.5 percent of margin of victory. The solid curves are plotted non-parametrically using local linear regression which uses a triangular kernel and the optimal bandwidth criterion proposed by Imbens and Kalyanaraman (2012). Positive margins of victory indicate a constituency in which a criminally accused candidate won against a non-accused candidate (the runner-up), while a negative margin shows that she/he was the runner-up and that the winner was not criminally accused. The RD figure shows a sharp difference in the average yearly growth of night lights at the cutoff ($MARGIN = 0$). The vertical difference between the red and blue lines reflects the estimated causal effect of electing a criminally accused candidate on yearly growth of night lights. In particular, at the cutoff, there is a statistically significant and negative effect of electing a criminally accused candidate.

We use a local linear regression with an optimal bandwidth (h) calculated using the criterion proposed by Imbens and Kalyanaraman (IK) algorithm to estimate the RD effect (equation 1) in column (1) of Table 2. This is our main specification and analogous to the Figure 3. The rest of the columns present these results using alternate bandwidths. We find a statistically negative effect of electing criminally accused candidates: the annual growth of night lights is approximately 24 percentage points lower in constituencies that barely elect a criminally accused candidate as compared to those constituencies that barely elected a candidate without accusations. In column (2), we use a bandwidth calculated using the Calonico, Cattaneo and Titiunik (2014) (CCT) algorithm, while in columns (3)-(4) we halve and double the IK bandwidth, respectively. The results in column (2) is quantitatively identical to those in column (1). Halving the bandwidth in column (3) results in a slightly larger estimate, while doubling the bandwidth in column (4) leads to a smaller estimate. Overall, the results remain statistically significant and similar in magnitude.

As discussed in Section 4, we use the intensity of night lights as a proxy for economic activity. It is, however, unclear what is driving the changes in night lights. For example, growth in night lights could represent changes in the supply of electricity. Alternately, it could be attributable to changes in demand. Irrespective of whether these changes are supply or demand-side driven, economic activity and the intensity of night lights should be correlated (although certainly not one-to-one). While we currently interpret these results in terms of night light intensity, we compute below the corresponding decline in GDP using existing estimates of the elasticity of growth of night lights to the growth of GDP.

In sum, we find a large negative and casual impact of electing a criminally accused politician in close election and these costs accumulate over time.

5.2 Robustness

In this section, we perform further robustness check using alternate functional forms, alternate definitions of the dependent variable. We also re-estimate our main result after controlling for covariates in the RD regression (similar to Meyersson 2014), and finally examine the impact of top coding on our results.

5.2.1 Sensitivity Analysis of RD Specification

While earlier researchers emphasized the analysis of different bandwidths (Imbens and Lemieux 2008), recent studies broaden the focus to also examine alternate control functions (Dell 2010, Lee and Lemieux 2009, Meyersson 2014). We address this in Appendix Table A-3 and A-4.

In Appendix Table A-3, we report the RD effects for quadratic, cubic, and quartic functions using the IK (h), CCT, h/2, and 2h bandwidth choices. In Appendix Table A-4, we present the

RD estimates using alternate bandwidth choices, specifically $0.9h$, $1.3h$, $1.7h$, $2.1h$, where $h(IK) = 6.35$.[36] Variations in the polynomial order in the control function are ordered by row and bandwidth choices by column in this table.

By and large, we find that the RD estimates are negative and statistically significant and qualitatively consistent with the main result in Table 2. Statistical significance, however, is lost when the bandwidth is large and the polynomial order of the control function is low.

5.2.2 Alternate Dependent Variables

Since night lights and their distribution can be measured in several ways, we explore here three alternate definitions of the dependent variable: the intensity of night lights in levels [$Log(Night\ Lights)$], the proportion of lit villages ($Proportion\ of\ Lit\ Villages$), and the growth of night lights averaged over the election term of the candidate ($Average\ Growth\ over\ the\ Election\ Term$). We present the estimates from RD effect for the three dependent variables in Appendix Table A-5. The graphical illustration of the RD effect and balance test is shown in Panels (a) and (b) of Appendix Figure A-1 for $Log(Night\ Lights)$, while Panels (c) and (d) presents the same for $Proportion\ of\ Lit\ Villages$.

While we focus on yearly growth of night lights (for better comparison across constituencies), both growth rates and levels are used when researchers talk about growth. Moreover, large percentage changes due to a small initial level can mask very small absolute changes. We therefore estimate the local linear RD regression using IK bandwidth for night lights in levels and present the results in column (1).

Our second measure is the proportion of lit villages within a constituency, which is the proportion of villages with detectable levels of light output in a given year. This measure provides an alternative way of quantifying the breadth of access to electricity within a constituency, compared to measures based on the level of light output alone. We present the estimate from local linear regression using IK bandwidth in column (2).

Finally, we consider growth of night lights averaged over the election term of the candidate. This is because our main dependent variable uses year to year variation in the growth of night lights in a constituency which could potentially be influenced by year to year volatility. We present the

[36] We repeat the same exercise for four additional bandwidths (i.e. 2.5, 5.0, 7.5, and 10.0) and find similar results. The table is available upon request.

estimate in column (3).

Results from Appendix Table A-5, columns (1)-(3) suggest that the point estimates remain statistically significant and negative using the alternate definitions of the dependent variable.

5.2.3 Controlling for Covariates

In a RD framework, there is no need to control for covariates since they are equal across the cutoff by assumption. However, it is possible to directly control for the covariates and estimate the local linear RD regression using IK bandwidth. We present the results in Appendix Table A-6, where additional controls are added as we move from column (1) to (3).

In column (1), we present the RD regression result without any controls, with state and year fixed effects in column (2), and add constituency and candidate's characteristics (for e.g. growth of night lights in t-1, growth of night lights in t-2, electorate size, numbers voted, total turnout, ruling party, SC constituency, ST constituency, gender, education, asset, and liabilities of winner and runner-ups) in column (3).

Our main result remains negative and statistically significant; however the size of the coefficient is slightly smaller than the one estimated in Table 2, column (1).

5.2.4 Top Coding

As previously noted, the night light data is censored at 63. While this is not an issue in less developed areas, this could be an issue in the wealthiest and most populated areas. In these areas, we cannot observe any changes above an intensity of 63. Although this is unlikely to be systematically correlated with the accusation of elected candidates, we directly address this in Appendix Table A-7. In Panel A, we drop any observations where the constituency-year pixel average is 63. In Panel B, we drop any constituency in which the average pixel intensity for any year is 63. In both cases, the results are both qualitatively and quantitatively similar to our earlier results.

5.3 Underlying Causes

In the previous section, we demonstrate the costs associated with electing accused politicians in close elections and the robustness of these results. We believe that the negative effect is attributable to the accused candidates.

We begin by examining whether the costs of electing accused politicians vary based on the underlying charges. If accused politicians are the underlying cause, we would expect that both the type of charge and the number of underlying cases would matter. In Table 3, we consider the effects of financial and serious crimes. In columns (1)-(4) of Panel A, we estimate the RD effect of electing candidates accused of financial charges on the yearly growth of night lights. In particular, we compare constituencies with a winner who is accused of at least 1 financial charge (and a loser who is not accused) to constituencies with a non-accused winner (and a loser who has at least 1 financial charge). Similarly, in columns (5)-(8), we examine the effect of electing candidates accused of only non-financial crimes where we compare constituencies with a winner who is accused of at least 1 crime but has no financial charge (and the runner up is not accused) to constituencies with a non-accused winner (and a runner up with at least 1 accusation but no financial accusation). We perform a similar analysis with serious charges in Panel B. We find consistent results: the type of charge matters. The coefficients for both financial and serious crimes are consistently significant and greater in magnitude than those estimated for any charge in column (1) of Table 2. In contrast, non-financial and non-serious charges are uniformly insignificant.

In Table 4, we examine the influence of the number of criminal cases. Higher numbers of cases can be viewed as a "higher intensity treatment" and, insofar as there are costs to filing false charges, may be more likely to represent "true" accusations. In columns (1)-(4) we present the results of the impact of electing a candidate with two or more charges, while in columns (5)-(8) present the results for candidates accused of five or more charges. Similar to the results with financial and serious charges, the number of criminal cases has a clear effect. The estimated coefficients are consistently significant and greater than the effect for any charge [column (1) in Table 2].[37] Taken together, the results from Tables 3 and 4 demonstrate that the characteristics of the candidate, specifically the candidate's accusation record, underlie the earlier results.

We next examine whether the effect of electing accused politicians varies across the years of a politician's term. That is, does the effect begin immediately after the election (the first year of the term) and remain constant throughout the term or does it vary across years? In Table 5, we estimate

[37] We estimate similar models using 2 and more financial (serious) charges and 5 or more financial (serious) charges. The results are qualitatively similar to those in Table 4. The results are available in Appendix Table A-2.

the effect of elected an accused candidate separately for each year of the term. The results show that the negative effect does not appear instantaneously. There are no effects in the first and second year. In contrast, the estimated coefficients are significant in years 3 and 4, and the magnitude and significance of the coefficient increases over time.

We interpret these findings to mean that the election of criminally accused politicians does not instantaneously result in lower economic activity. For politicians to engage in corrupt behavior, they require collaboration with local bureaucrats (Iyer and Mani 2012). Consequently, a certain amount of time is necessary for corrupt politicians and bureaucrats to form a nexus and to engage in corrupt activity. For example, the effect of neglected public infrastructure, such as roads etc., may take some time to slow down economic activity.

Our above results are based on night lights as a measure of economic activity. We next examine an alternate measure of economic development and a proxy for public good provision: the number of incomplete road projects in the constituency. We choose road projects because the number of incomplete projects in a constituency is likely to be uncorrelated with the supply or growth of electricity. At the same time, corruption is widely believed to be rampant in India's highway construction (WSJ, 2012).[38] This corruption often involves the manipulation of the tenders and the process of procurement, often leading to lower quality and unfinished road projects. For instance, a senior official reported that "road mafias" of contractors, engineers, the local police, civil servants, "and last but not least local politicians", conspire to keep prices on road contracts above market rates (Singh 2005).[39] In explaining roads sector corruption in the state of Jharkhand (a so-called BIMAROU state), a civil society activist told the New York Times that "the nexus of politicians, contractors and bureaucrats is very strong" (Polgreen 2010).[40]

We use data from Pradhan Mantri Gram Sadak Yojana (PMGSY) program, a rural roads construction program which forms an integral part of the Government's poverty reduction strategy. Under PMGSY about 360,000 kms of rural roads are being constructed with a projected investment of approximately US $14 billion for construction and US $9 billion for "upgradation" of existing tracks.

[38] `http://blogs.wsj.com/indiarealtime/2012/05/04/road-building-still-tarred-with-corruption/`.

[39] Eynde and Lehne (2015) finds evidence for political corruption in PMGSY. In particular, by matching local politicians to the contractors active their constituencies-based on their last names, they find that politicians appear to be intervening in the allocation of contracts on behalf of members of their own network.

[40] `http://www.nytimes.com/2010/06/29/world/asia/29india.html`.

We present the RD effects from the local linear regression using an IK bandwidth by the type of accusation and state characteristics in Table 6. In Panel A, we report the results for the number of incomplete road projects for any accusation [similar to Table 2, column (1)], while Panel B reports the result by serious accusation, and Panel C by financial accusation. We find that the number of incomplete road projects increases in constituencies represented by criminally accused candidates and that the magnitude of the RD estimate is larger when we consider candidates accused of serious and financial charges. When we consider the impact of electing criminally accused candidates and candidates accused of serious and financial charges in constituencies belonging to BIMAROU, Least Developed, and High Corruption states, we find that the number of incomplete projects is approximately *three* times higher in High Corruption and Least Developed states as compared to the sample consisting of all states cColumn (4) compared to column (1) in Panels A-C].[41]

Taken together, these results support the hypothesis that criminally accused politicians have an adverse effect on economic activity in their constituencies. Politicians accused of certain types of crimes or accused of multiple crimes have a particularly detrimental impact, implying that a politician's type matters.

5.4 State Characteristics

We now examine how the effect of electing criminally accused varies by different state characteristics. First, we consider the so-called "BIMAROU" states of Bihar, Jharkhand, Odisha, Uttar Pradesh, and Uttarakhand (The acronym BIMAROU is formed using the first letters of the word 'sick': in Hindi). These states are widely considered to be lagging behind in terms of economic development and have been singled out for being corrupt and generally dysfunctional. Second, we consider the set of states that the Ministry of Finance has classified as "least developed": Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh. Finally, using measures of corruption created by Transparency International India's (TII), drawn from the India Corruption Study of 2005, we classify states into "High-Corruption" and "Low-Corruption" states.

We present the results in Table 7. The RD estimate for "BIMAROU" states are reported in

[41]We present the graphical illustration of the RD effect for the number of incomplete road projects, and results from the balance test in Appendix Figure A-2. We repeat the same analysis for share of incomplete road projects and find similar result. The RD figure, regression result, and the balance test is available upon request.

column (1), while column (2) reports the estimate for "Least Developed" states, and finally column (3) reports the estimate for "High-Corruption" states. These effects are negative and statistically significant. The size of the coefficients for "BIMAROU" and "Least Developed" states are roughly one and a half times larger than our main result [Table 2, column (1)] and slightly more than double for high corruption states [The coefficient is -24.05 for our baseline result (all states), -44.92 for least developed states, and -55.70 for High-Corruption states]. However, the results are statistically insignificant for "Non-BIMAROU", "Relatively Developed" and "Low Corruption" states as reported in columns (1)-(3) of Appendix Table A-8.

Since there is substantial overlap between the states in the "BIMAROU", "Least Developed" and "High Corruption" classifications, it is difficult to isolate one particular factor. Rather, we see that the effects of electing accused politicians are largely confined to constituencies located within particular types of states. One common feature of these states is the relatively weaker institutions whether judicial, police or other aspects. Anecdotal evidence suggests that in states with stronger institutions, the actions of criminal politicians are more constrained. In contrast, those states with lower quality institutions have reputations (arising from many examples) of lawless behavior and general impunity for politicians and bureaucrats. Thus, a criminally accused politician is more likely to compromise governance where institutions are less developed.

6 Back of the Envelope Calculation

In the previous sections, we interpret the change in the intensity of night lights as a proxy for economic activity. It is possible, however, to obtain a *rough* estimate of the direct effect by using the elasticity for the effect of night lights intensity on GDP growth. We use two alternate measures of elasticity. We use the elasticity of 0.3 estimated by Henderson et al. (2012) for a global sample of low and medium income countries. We supplement this with Bickenbach et al.'s (2013) India-specific district-level estimate of elasticity of 0.107. Since there are no reliable and systematic figures for growth at the constituency level (as we would have used these), this represents the most disaggregated analysis of the elasticity for India. These two estimates provide us with an upper-and lower-bound respectively for our rough estimate of the effect on GDP growth.

We present the "back of the envelop calculations" of GDP loss in Table 8. In column (1), we calculate the impact of electing an accused candidate in terms GDP loss [i.e. for our main result as reported in Table 2, column (1)]. We present the same estimate for candidates accused of at least one financial charge in column (2), and finally for candidates accused of at least one serious charge in column (3).[42]

Depending on the type of criminal accusation, we find estimates ranging from 2.6 percentage point lower GDP growth per year using elasticity from India. India experienced very high growth during this period, ranging from 7.9-percent in 2003 to 9.8-percent in 2007. Since these are estimates of the yearly cost, the foregone growth over the entire term is larger as these losses compound over the full 5 year term. Using a more conservative estimate of 6-percent GDP growth as a measure of the average yearly constituency growth, this would imply that, on average, electing an accused candidate would result in a 5.18 to 5.85-percent GDP growth per year (as compared to the 6-percent otherwise).

These rough estimates of the cost in terms of GDP growth raise parallel questions in terms of the foregone poverty reduction and the effects on distribution. While the data do not exist to verify this, it is important to highlight that these are not just aggregate constituency-level costs; they are likely commensurate micro-level costs.

Lastly, the RD design allows for the estimation of a causal relationship, the estimated impact is only valid near the discontinuity, i.e. our estimates are local average treatment effect (LATE). That is, these are the losses associated with the election of criminally accused politicians in very close elections.

7 Conclusions

In this paper, we estimate the economic costs of electing criminally accused politicians at the constituency level by using data on the intensity of night lights and sworn affidavits of candidates on their criminal background. We find a large negative and causal impact as the yearly growth of night lights declines by 24 percentage points. The estimated effect is not just statistically significant but economically meaningful. In particular, we find that constituencies that elect criminally accused

[42] We cannot investigate the impact on alternate dependent variable since the elasticities are only available for the intensity of night lights.

politicians experience 2.6-percentage point lower GDP growth per year in the Indian states [Table 8, column (1)]. This effect is more pronounced depending on the nature of the criminal accusation of the elected representative (for example, serious and financial criminal charge vs. any criminal charge) and for states associated with high perception of corruption, least developed, and plausibly with weaker institutions (for example, BIMAROU).

Although we cannot identify the exact channels, the results strongly suggest that this is due to criminal activity by the candidates. In particular, this effect is largely driven by candidates with serious and financial charges and the effect increases with the number of criminal cases. The results suggest that the behavior of criminals affects economic activity in their constituencies. Politicians who are accused of specific charges (serious or financial) have a disproportionately large negative effect.

Using data on incomplete road projects, we find strong evidence that a lower number of road projects are completed in constituencies that elected criminally accused candidates to state assemblies in India. This provides important evidence of lower public good provision (insofar as road projects are a good proxy). Since investments in road projects, schools, and hospitals take time, it is not surprising that the negative impact accumulates after some time. This is also consistent with results in Table 5, where we show that the negative impact is driven in the second half of the state legislator's term in public office.

More broadly, our results suggest the importance of the joint effect of the quality of candidate and the local context. If true, this suggests two potential pathways to address the problem. If the quality of the candidates cannot be improved, the local context (especially the institutional and legal context) can be strengthened to constrain the adverse effects of lower quality candidates.

Although we study a particular context, lower quality politicians are believed to be pervasive in many developing countries. While the underlying cause if often context-specific and may range from caste-politics to tribal and ethnic voting, we believe that our analysis is suggestive for these contexts. These areas are often characterized by lower development outcomes. While these lower outcomes may contribute to the election of lower quality candidates, our results suggest that their election may similarly lead to lower outcomes.

Our results are particularly relevant for policy makers in many developed and developing countries who are grappling with similar situations. Therefore, 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-A

Descriptive Statistics of Dependent Variables

	RD Sample			Close Elections (difference in share <5%)		
Variables	Accused	Non-Accused	Difference	Accused	Non-Accused	Difference
Growth of Night Lights in t+1	2.04	2.43	-0.39	-1.79	1.36	-3.15
	(75.60)	(98.60)	(2.90)	(83.00)	(88.00)	(4.88)
Log of Night Lights in t+1	11.00	11.00	0.02	10.80	11.00	-0.13
	(1.84)	(1.83)	(0.06)	(1.75)	(1.83)	(0.10)
Proportion of Lit Villages in t+1	0.72	0.71	0.02	0.68	0.71	-0.035*
	(0.33)	(0.34)	(0.01)	(0.34)	(0.36)	(0.02)
No. of observations	1915	1701		611	616	
Number of Incomplete Road Projects	0.62	0.71	-0.10	0.60	0.68	-0.08
	(2.91)	(3.11)	(0.11)	(3.23)	(2.88)	(0.19)
No. of observations	1591	1396		518	549	

Notes: Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 1-B

Descriptive Statistics of Pre-determined Characteristics

	RD Sample			Close Elections (difference in share <5%)		
Variables	Accused	Non-Accused	Difference	Accused	Non-Accused	Difference
Growth of Light in Previous Year	16.00	30.80	-14.9**	27.90	35.40	-7.50
	(75.50)	(140.30)	(7.23)	(91.60)	(133.90)	(12.90)
Number of Incomplete Road Projects in Previous Year	0.091	0.1	-0.012	0.058	0.083	-0.024
	(0.48)	(0.52)	(0.04)	(0.35)	(0.33)	(0.04)
Log of Night Lights in Previous Year	10.90	10.80	0.04	10.70	10.80	-0.13
	(1.61)	(1.65)	(0.11)	(1.41)	(1.46)	(0.16)
Proportion Lit Villages Previous Year	0.72	0.72	0.00	0.67	0.73	-0.06
	(0.34)	(0.34)	(0.02)	(0.35)	(0.34)	(0.04)
Log Electorate Size in Previous Election	12.00	12.10	-0.072**	12.10	12.10	0.00
	(0.49)	(0.42)	(0.03)	(0.43)	(0.38)	(0.05)
Log Number Voted in Previous Election	11.50	11.60	-0.071***	11.60	11.60	-0.02
	(0.45)	(0.38)	(0.03)	(0.37)	(0.35)	(0.04)
Turnout in Previous Election	64.30	64.40	-0.10	63.10	64.40	-1.24
	(10.50)	(11.40)	(0.71)	(10.30)	(11.00)	(1.20)
Log Winners Assets	14.90	14.90	0.00	14.80	15.00	-0.25
	(2.10)	(1.90)	(0.13)	(2.27)	(1.56)	(0.22)
Log Winners 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 Runners-up Assets	14.85	14.71	0.14	14.78	14.92	-0.14
	(2.11)	(2.15)	(0.14)	(2.30)	(1.77)	(0.23)
Log Runners-up Liability	7.31	6.92	0.39	6.94	6.88	0.06
	(6.43)	(6.42)	(0.42)	(6.56)	(6.48)	(0.73)
Winners Gender in Previous Election	0.07	0.05	0.02	0.08	0.07	0.01
	(0.26)	(0.22)	(0.02)	(0.26)	(0.25)	(0.03)
Runners-up Gender in Previous Election	0.07	0.05	0.02	0.06	0.04	0.01
	(0.25)	(0.21)	(0.02)	(0.23)	(0.21)	(0.03)
Winners Education	2.22	2.48	-0.26***	2.36	2.37	-0.01
	(1.19)	(1.15)	(0.08)	(1.15)	(1.21)	(0.13)
Runners-up Education	2.35	2.21	0.14*	2.44	2.26	0.18
	(1.25)	(1.20)	(0.08)	(1.23)	(1.19)	(0.14)
SC Constituency	0.11	0.13	-0.03	0.11	0.08	0.03
	(0.31)	(0.34)	(0.02)	(0.31)	(0.26)	(0.03)
ST Constituency	0.05	0.05	0.00	0.03	0.03	0.01
	(0.22)	(0.22)	(0.01)	(0.18)	(0.16)	(0.02)
Ruling Party in Previous Election	0.52	0.57	-0.05	0.47	0.50	-0.03
	(0.50)	(0.50)	(0.03)	(0.50)	(0.50)	(0.06)
Incumbent in Previous Election	0.36	0.44	-0.081**	0.36	0.38	-0.02
	(0.48)	(0.50)	(0.03)	(0.48)	(0.49)	(0.05)
No. of observations	503	438		159	159	

Notes: Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 1-C

Descriptive Statistics of Criminal Accusations

	RD Sample				**Close Elections (difference in share <5%)**			
Variables	All	Winners	Runners-up	Difference	All	Winners	Runners-up	Difference
Any case	50.00	53.50	46.50	7.00***	50.00	50.00	50.00	0.00
	(0.50)	(0.50)	(0.50)	(0.02)	(0.50)	(0.50)	(0.50)	(0.04)
Any serious charge	37.40	40.20	34.60	6.00**	37.40	39.60	38.50	-2.20
	(0.48)	(0.49)	(0.48)	(0.02)	(0.49)	(0.48)	(0.49)	(0.04)
Any financial charge	18.00	19.40	16.50	3.00*	16.70	17.90	17.30	-1.26
	(0.38)	(0.40)	(0.37)	(0.02)	(0.38)	(0.37)	(0.38)	(0.03)
Multiple charge (>1)	24.30	27.30	21.30	6.00***	24.50	26.40	25.50	-1.89
	(0.43)	(0.45)	(0.41)	(0.02)	(0.44)	(0.43)	(0.44)	(0.03)
Avg. number of serious charges	1.33	1.47	1.19	28.00*	1.61	1.66	1.64	-5.35
	(3.57)	(3.43)	(3.70)	(0.16)	(5.18)	(4.66)	(5.65)	(0.41)
Avg. number of financial charges	0.18	0.19	0.16	3.00*	0.17	0.18	0.17	-1.26
	(0.38)	(0.40)	(0.37)	(0.02)	(0.38)	(0.37)	(0.38)	(0.03)
No. of observations	1882	941	941		636	318	318	

Notes: Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 2

Effect of Electing Criminally Accused Politicians on Growth of Night Lights

Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
Criminally Accused	-24.05**	-22.55**	-24.90*	-14.50**
	(9.86)	(8.94)	(14.35)	(6.09)
State and Year Fixed Effects	YES	YES	YES	YES
Bandwidth Size	6.35	7.32	3.17	12.70
No. of observations	1,581	1,728	783	2,543
Polynomial order of control function	Local Linear			
Bandwidth Type	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of year growth of night lights on state and year dummies. Criminally accused 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)–(4) are on a local linear regression using a triangular kernel.

Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 3

Effect of Electing Criminally Accused Politicians by Accusation Type

Dependent Variable	**Growth of Night Lights**							
Type of Accusation	Financial Charge				Non-Financial Charge			
Polynomial order of control function:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PANEL A							
Local Linear	-45.80***	-43.64***	-37.14*	-23.81**	-9.86	-10.48	-16.12	-4.76
	(16.19)	(15.42)	(19.37)	(10.59)	(8.96)	(9.57)	(15.77)	(5.30)
Bandwidth Size	7.72	8.41	3.86	15.44	8.97	8.19	4.48	17.94
No. of observations	611	653	306	958	1,332	1,249	724	1,976
	PANEL B							
Type of Accusation	Serious Charge				Non-Serious Charge			
Local Linear	-33.02**	-32.63***	-29.41*	-23.38***	9.33	9.23	3.37	0.46
	(12.79)	(11.37)	(16.93)	(8.34)	(6.88)	(6.85)	(7.62)	(4.73)
Bandwidth Size	5.49	6.78	2.75	10.99	7.38	7.78	3.69	14.75
No. of observations	1,070	1,257	506	1,729	422	426	226	707
State and Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Bandwidth Type	IK (h)	CCT	h/2	2h	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Results displayed in each panel-column come from a separate regression. In Panel A, columns (1)–(4) criminally accused is 1 for a winner who is accused of a financial crime and ran against a non-criminally accused loser; and 0 for a loser who is accused of a financial crime and ran against a non-criminally accused winner. In columns (5)–(8) criminally accused is 1 for a winner who is accused of a non-financial crime and ran against a non-criminally accused loser; and 0 for a loser who is accused of a non-financial crime and ran against a non-criminally accused winner. In Panel B, columns (1)–(4) criminally accused is 1 for a winner who is accused of a serious crime and ran against a non-criminally accused loser; and 0 for a loser who is accused of a serious crime and ran against a non-criminally accused winner. In columns (5)–(8) criminally accused is 1 for a winner who is accused of a non-serious crime and ran against a non-criminally accused loser; and 0 for a loser who is accused of a non-serious crime and ran against a non-criminally accused winner.

Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 4

Effect of Electing Criminally Accused Politicians by Multiple Cases

Dependent Variable	**Growth of Night Lights**							
Type of Accusation	Multiple Cases (>= 2)				Multiple Cases (>= 5)			
Polynomial order of control function:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Linear	-34.03***	-33.41***	-28.23**	-20.80***	-48.49**	-45.54**	-51.75*	-30.16*
	(11.45)	(11.15)	(12.80)	(7.89)	(21.69)	(20.78)	(27.84)	(15.86)
Bandwidth Size	6.96	7.39	3.48	13.93	7.83	8.71	3.92	15.66
No. of observations	815	842	413	1,245	238	253	122	351
Bandwidth Type	IK (h)	CCT	h/2	2h	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Results displayed in each column come from a separate regression. In columns (1)–(4) criminally accused is 1 for a candidate who is accused of 2 or more criminal cases; and 0 otherwise. In columns (5)–(8), criminally accused is 1 for a candidate who is accused accused of 5 or more criminal cases.

Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 5

Effect of Electing Criminally Accused Politicians by Year in Power

Dependent Variable	**Growth of Night Lights**			
	$Log(Y_{ist+1}) - Log(Y_{ist})$	$Log(Y_{ist+2}) - Log(Y_{ist})$	$Log(Y_{ist+3}) - Log(Y_{ist})$	$Log(Y_{ist+4}) - Log(Y_{ist})$
	(1)	(2)	(3)	(4)
Criminally Accused	-4.52	-12.88	-56.08*	-104.12**
	(7.99)	(11.21)	(33.32)	(45.65)
State and Year Fixed Effects	YES	YES	YES	YES
Bandwidth Size	9.71	7.3	4.69	5.61
No. of observations	552	442	289	331
Polynomial order of control function	Local Linear			
Bandwidth Type	Imbens-Kalyanaraman			

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Criminally accused 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)–(4) are based on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 6

Effect of Electing Criminally Accused Politicians on Incomplete Road Projects

Dependent Variable	**Number of Incomplete Road Projects**			
Sample Type	All States	BIMAROU States	Least Developed States	High Corruption States
	(1)	(2)	(3)	(4)
	Panel A			
Criminally Accused	0.85*	1.83**	1.89**	2.75**
	(0.48)	(0.85)	(0.89)	(1.33)
Bandwidth Size	4.34	4.29	4.39	4.42
No. of observations	916	426	434	317
	Panel B			
Serious Charge	1.07*	2.11**	2.02**	2.99**
	(0.55)	(0.94)	(0.93)	(1.48)
Bandwidth Size	4.04	4.36	4.86	4.39
No. of observations	690	381	416	276
	Panel C			
Financial Charge	0.91	2.27*	2.30*	1.61
	(0.63)	(1.16)	(1.16)	(1.15)
Bandwidth Size	5.33	4.58	4.59	4.82
No. of observations	389	173	177	173
State and Year Fixed Effects	YES	YES	YES	YES
Polynomial order of control function	Local Linear			
Bandwidth Type	Imbens-Kalyanaraman			

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Criminally Accused, Serious Charge, and Financial Charge is constructed as in Tables 2 and 4. The definitions of BIMAROU, Least Developed, and High Corruption states remains same as Table 6.
Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 7

Heterogeneous Effect of Electing Criminally Accused Politicians by State Characteristics

Dependent Variable	**Growth of Night Lights**		
Sample	BIMAROU States	Least Developed States	High Corruption States
	(1)	(2)	(3)
Criminally Accused	-43.33**	-44.92**	-55.70**
	-19.54	(21.51)	(25.26)
Bandwidth Size	5.37	5.06	6.55
No. of observations	563	535	485
State and Year Fixed Effects	YES	YES	YES
Polynomial order of control function	Local Linear		
Bandwidth Type	Imbens-Kalyanaraman		

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Results displayed in each column come year from a separate regression. In column (1) the BIMAROU states include Bihar, Chattisgarh, Jharkhand, Orissa, Uttar Pradesh, and Uttarakhand. Column (2) include least developed states as ranked by Ministry of Finance. Least-developed states include Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh. In column (3) we use states as ranked by Transparency International India (TII) on index of corruption. High corruption states include Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar; while low corrupt states include Kerala, Himachal Pradesh, Gujarat, Maharashtra, Punjab, West Bengal, Orissa and Uttar Pradesh.
Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE 8

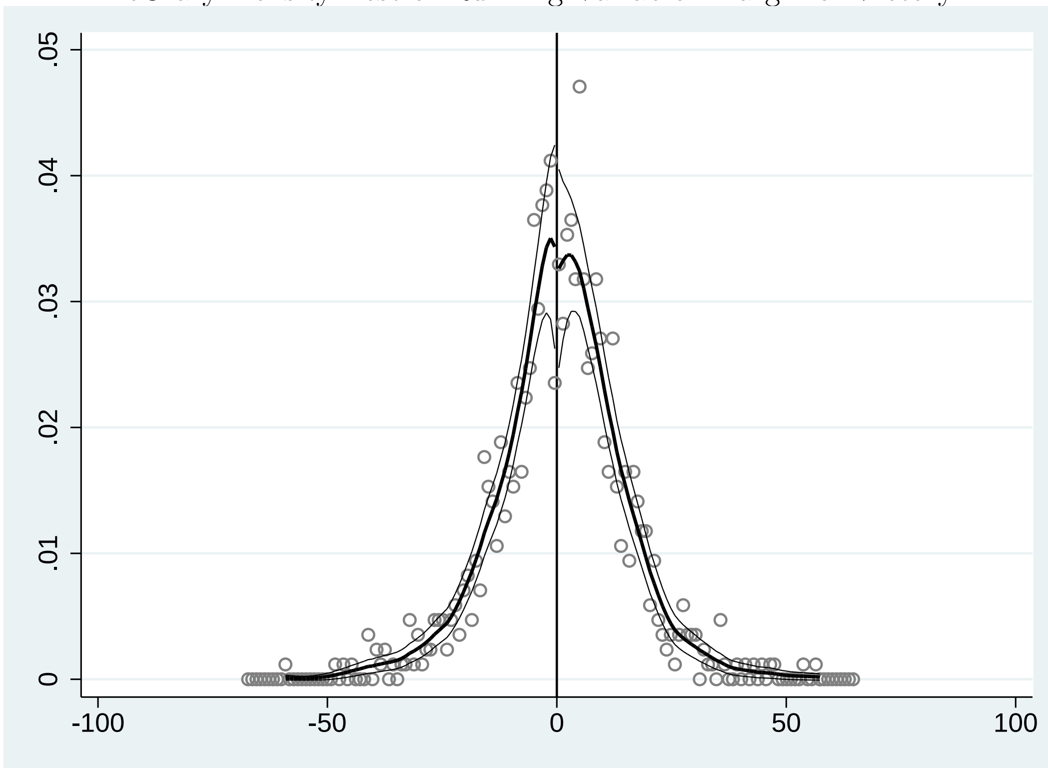
Effect of Electing Criminally Accused Politicians on Constituency GDP Growth

Dependent Variable	**Growth of Night Lights**		
	Baseline Estimate	Financial Charge	Serious Charge
	(1)	(2)	(3)
RD Estimate	-24.05	-45.8	-33.02
Polynomial order of control function		Local Linear	
Bandwidth type		Imbens-Kalyanaraman	
	Estimated Effect on GDP Growth Rate (in percentage points)		
Using global average (Henderson et al. 2014)	-7.2	-13.7	-9.9
Using India-specific average (Bickenback et al. 2014)	-2.6	-4.9	-3.5
	Assuming 6% growth - what would growth look like?		
Upper Bound	5.57	5.18	5.41
Lower Bound	5.85	5.71	5.79

Notes: The definition of the main explanatory variable changes across the columns: criminally accused, financial criminal accusation, and serious criminal accusation. Column (1) reports the RD estimate for criminally accused from Table 2, Column (1). In Column (2), we report the RD estimate for any financial charge from Column (1) of Table 4, Panel A, while we report the RD estimate for any serious charge from Column (1) of Table 4, Panel B in Column (3) of this table. The upper-bound uses an elasticity of 0.3. The lower-bound uses an elasticity of 0.107.

Figure 1

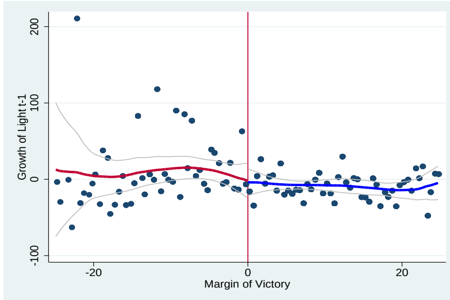
McCrary Density Test of Running Variable: Margin of Victory



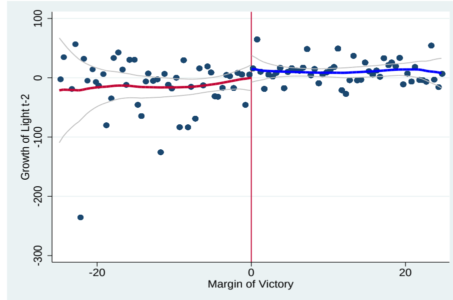
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. The estimated size of discontinuity in margin of victory (log difference in height) is -0.061 (se = 0.2).

Figure 2

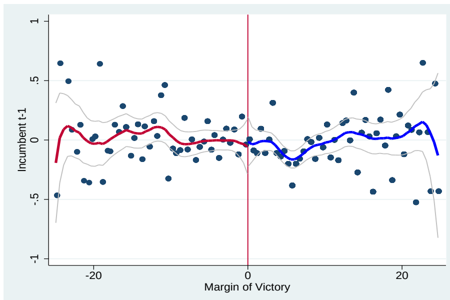
Pre-determined Characteristics: Continuity Checks



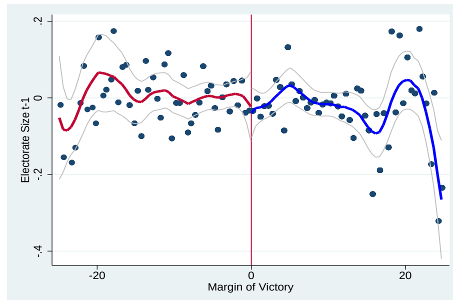
(a) Growth of Light t-1



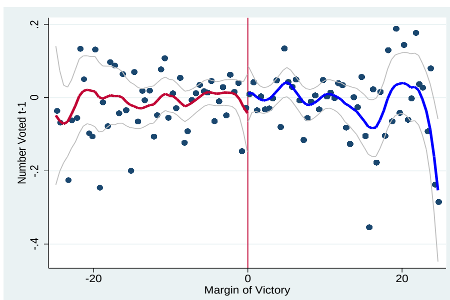
(b) Growth of Light t-2



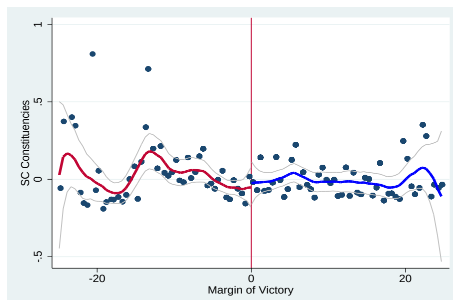
(c) Incumbent in t-1



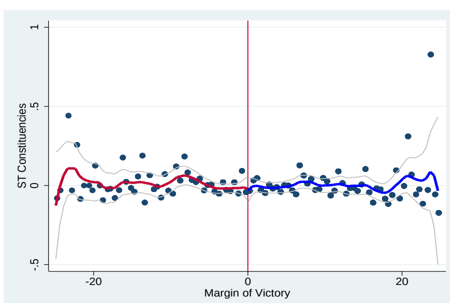
(d) Electorate Size t-1



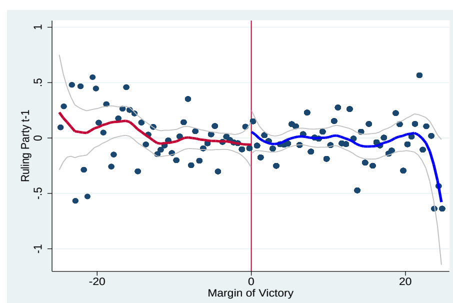
(e) Number Voted t-1



(f) SC Constituencies



(g) ST Constituencies

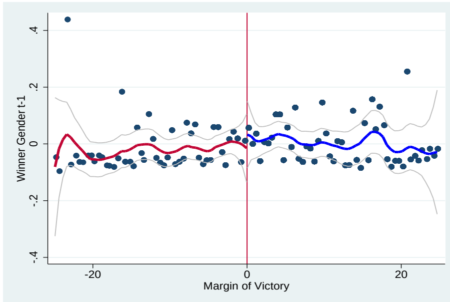


(h) Ruling Party t-1

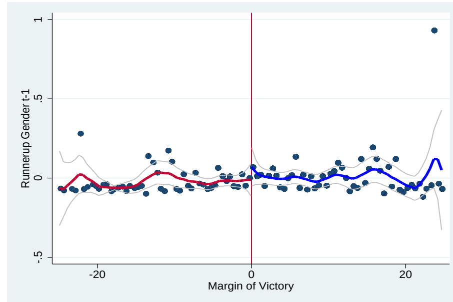
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. 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 triangular 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 2

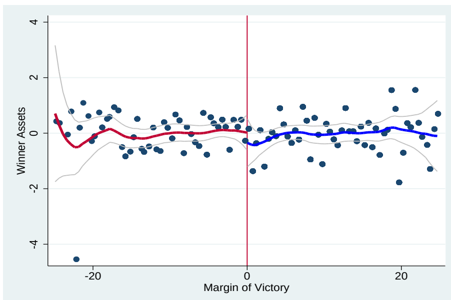
Pre-determined Characteristics: Continuity Checks (contd)



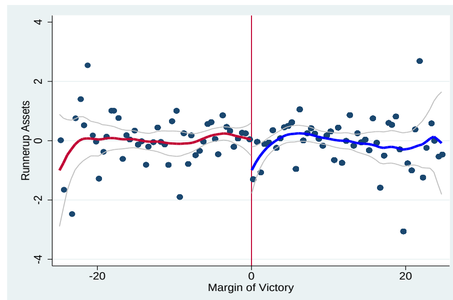
(i) Winners Gender t-1



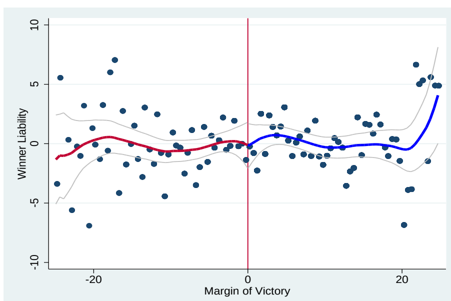
(j) Runners-up Gender t-1



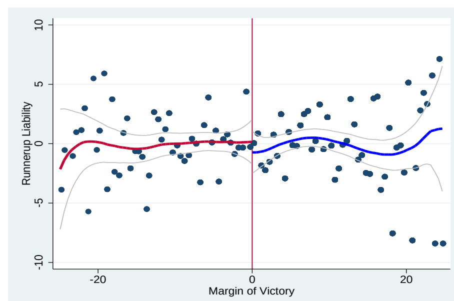
(k) Winners Assets



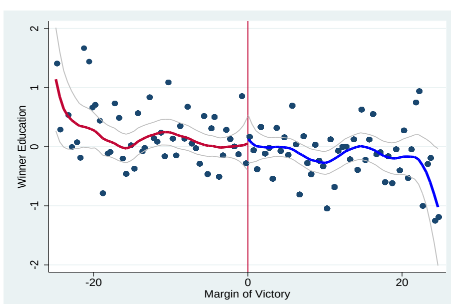
(l) Runners-up Assets



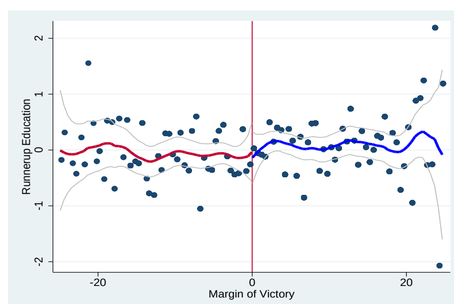
(m) Winners Liabilities



(n) Runners-up Liabilities



(o) Winners Education

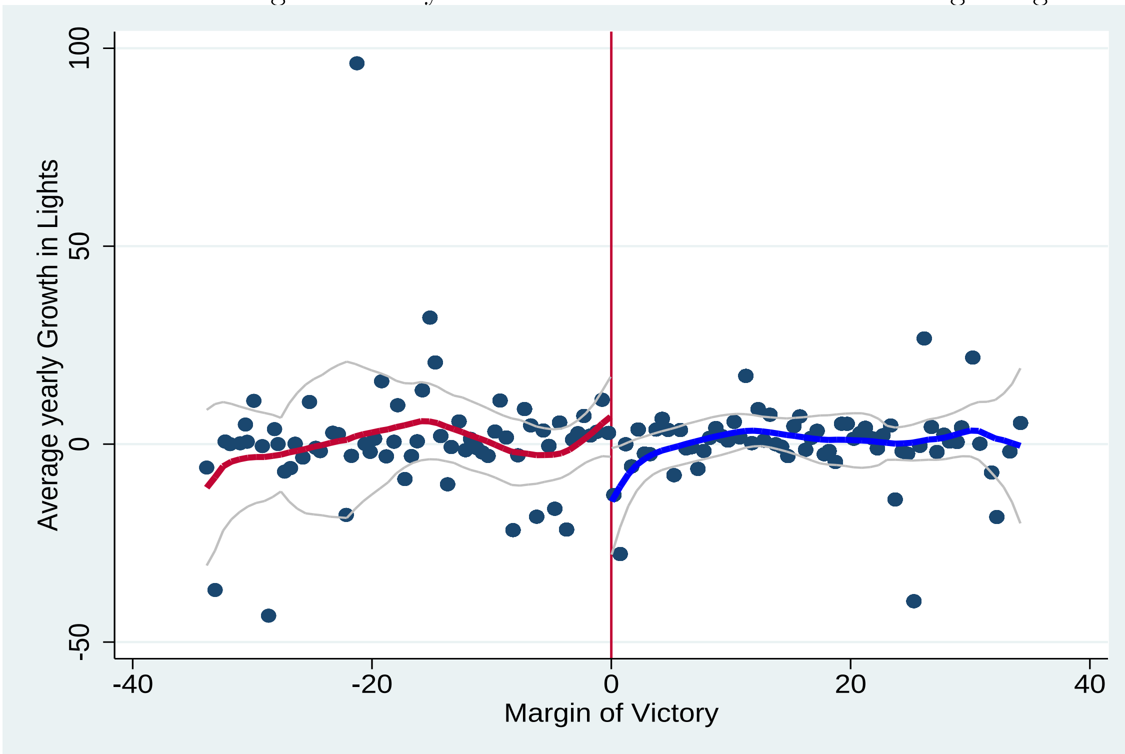


(p) Runners-up Education

The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. 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 triangular 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

Effect of Electing Criminally Accused Politicians on Growth of Night Lights



The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. The variable on the y-axis is the growth of night lights net of state and year fixed effects. The dots in the scatter plot depict the average of growth of night lights 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 triangular 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.

TABLE A-1

State Name and Year of Elections

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
Odisha	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	

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

TABLE A-2

Effect of Electing Criminally Accused Politicians by Accusation Type Thresholds

Dependent Variable	**Growth of Night Lights**							
Type of Accusation	Financial Charges (>= 2)				Financial Charges (>= 5)			
Polynomial order of control function:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				PANEL A				
Local Linear	-62.96***	-64.44***	-64.82**	-29.91**	-66.71*	-85.49**	-122.66***	-54.77**
	(20.24)	(20.63)	(29.82)	(13.34)	(32.89)	(37.67)	(38.09)	(22.96)
Bandwidth Size	9.29	9.05	4.64	18.57	16.22	13.37	8.11	32.44
No. of observations	331	320	180	490	113	97	74	140
				PANEL B				
Type of Accusation	Serious Charges (>= 2)				Serious Charges (>= 5)			
Local Linear	-29.51**	-29.52***	-18.01	-19.38**	-55.36**	-52.33***	-48.73*	-42.11***
	(11.87)	(11.03)	(11.75)	(8.03)	(21.20)	(19.62)	(24.70)	(15.77)
Bandwidth Size	6.11	7.18	3.06	12.22	7.25	8.59	3.62	14.50
No. of observations	840	910	431	1,271	323	353	184	434
State and Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Bandwidth Type	IK (h)	CCT	h/2	2h	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. The dependent variable is the residual from the regression of state and year dummies. Results displayed in each panel-column come from a separate regression. In Panel A, columns (1)–(4) criminally accused is 1 for a candidate who is accused of 2 or more financial charges; and 0 otherwise. In columns (5)–(8), criminally accused is 1 for a candidate who is accused accused of 5 or more financial charges. In Panel B, columns (1)–(4) criminally accused is 1 for a candidate who is accused of 2 or more serious criminal charges; and 0 otherwise. In columns (5)–(8), criminally accused is 1 for a candidate who is accused of 5 or more serious criminal charges. Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-3

Sensitivity Analysis of RD Specification by Polynomial order of Control Function

Dependent Variable	**Growth of Night Lights**			
Type of Accusation	Criminally Accused			
Polynomial order of control function:	(1)	(2)	(3)	(4)
Linear	-24.05**	-22.55**	-24.90*	-14.50**
	(9.86)	(8.94)	(14.35)	(6.09)
Bandwidth Size	6.35	7.32	3.17	12.70
No. of observations	1,581	1,728	783	2,543
Quadratic	-24.56*	-24.71**	-22.62	-24.99**
	(14.28)	(9.95)	(19.28)	(10.07)
Bandwidth Size	6.35	12.96	3.17	12.70
No. of observations	1,581	2,563	783	2,543
Cubic	-22.02	-27.05**	-15.26	-28.44**
	(17.75)	(11.48)	(22.91)	(13.46)
Bandwidth Size	6.35	17.45	3.17	12.70
No. of observations	1,581	2,989	783	2,543
Quartic	-24.51	-28.13**	-9.91	-24.49
	(20.85)	(12.73)	(24.43)	(15.91)
Bandwidth Size	6.35	21.93	3.17	12.7
No. of observations	1,581	3,254	783	2,543
State and Year Fixed Effects	YES	YES	YES	YES
Bandwidth type	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. Results displayed in each panel-column come from a separate regression that also controls for state and year fixed effects. Criminally accused 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.

Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-4

Sensitivity Analysis of RD Specification by Bandwidth

Dependent Variable	**Growth of Night Lights**			
Type of Accusation	Criminally Accused			
Polynomial order of control function:	(1)	(2)	(3)	(4)
Linear	-24.51**	-20.96**	-16.93**	-13.82**
	(10.57)	(8.24)	(6.85)	(5.88)
Quadratic	-23.39	-27.26**	-26.66**	-24.29**
	(15.03)	(12.80)	(11.06)	(9.77)
Cubic	-23.55	-22.87	-27.08*	-28.64**
	(18.44)	(16.10)	(14.34)	(13.14)
Quartic	-22.79	-20.96	-21.75	-25.35
	(21.55)	(18.82)	(17.05)	(15.58)
Bandwidth Size	5.72	8.26	10.80	13.34
No. of observations	1,446	1,899	2,285	2,594
State and Year Fixed Effects	YES	YES	YES	YES
Bandwidth Type	0.9h	1.3h	1.7h	2.1h

Notes: Standard errors are clustered at the constituency level and given in parentheses. Results displayed in each panel-column come from a separate regression that also controls for state and year fixed effects. Criminally accused 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. Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-5

Effect of Electing Criminally Accused Politicians by Alternate Dependent Variables

Dependent Variable	**Log(Night Lights)**	**Prop of Lit Villages**	**Avg Growth over the Election Term**
	(1)	(2)	(3)
Criminally Accused	-1.08***	-0.13**	-24.33**
	(0.41)	(0.06)	(10.53)
State and Year Fixed Effects	YES	YES	YES
Bandwidth Size	2.48	5.00	5.71
No. of observations	615	1,183	371
Polynomial order of control function		Local Linear	

Notes: Standard errors are clustered at the constituency level and given in parentheses. Results displayed in each column come year from a seperate regression. The dependent variable is the residual from the regression of state and year dummies. Log(Night Lights) is the intensity of night lights in levels; Proportion of Lit Villages is the proportion of villages with detectable levels of light output in a given year; and Average Growth over the Election Term is the growth of night lights averaged over the election term of the candidate.

Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-6

Controlling for Covariates

Dependent Variable	**Growth of Night Lights**		
	(1)	(2)	(3)
Criminally Accused	-20.46**	-18.20**	-18.37**
	(9.26)	(8.84)	(8.96)
State and Year Fixed Effects	NO	YES	YES
Pre-determined Characteristics	NO	NO	YES
Bandwidth Size	6.54	6.54	6.54
No. of observations	1,609	1,609	1,609
R-squared	0.00	0.15	0.17
Polynomial order of control function	Local Linear		
Bandwidth Type	Imbens-Kalyanaraman		

Notes: Standard errors are clustered at the constituency level and given in parentheses. In Columns (1)–(3), we add additional controls. In Column (3) we add constituency and candidate's characteristics. They are growth of night lights in t-1, growth of night lights in t-2, electorate size, numbers voted, total turnout, ruling party, SC constituency, ST constituency, gender, education, asset, and liabilities of winner and runners-up. Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-7

Does Top Coding Matter?

Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
Panel A: Dropping observations where constituency-year pixel = 63				
Criminally Accused	-24.10**	-22.72**	-24.79*	-14.43**
	(9.86)	(9.00)	(14.33)	(6.09)
Bandwidth Size	6.36	7.25	3.18	12.73
No. of observations	1,567	1,710	779	2,522
Panel B: Dropping any constituency with pixel intensity = 63				
Criminally Accused	-24.14**	-22.78**	-24.83*	-14.50**
	(9.88)	(9.03)	(14.34)	(6.10)
Bandwidth Size	6.35	7.22	3.18	12.7
No. of observations	1,561	1,700	779	2,511
State and Year Fixed Effects	YES	YES	YES	YES
Polynomial order of control function	Local Linear			
Bandwidth Type	IK (h)	CCT	h/2	2h

Notes: Standard errors are clustered at the constituency level and given in parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01)

TABLE A-8

Heterogeneous Effect of Electing Criminally Accused Politicians by State Characteristics

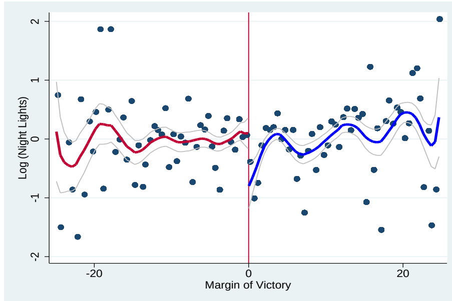
Dependent Variable	**Growth of Night Lights**		
Sample	Non-BIMAROU States	Relatively Developed States	Low Corruption States
	(1)	(2)	(3)
Criminally Accused	-5.03	0.95	-8.84
	(4.50)	(1.14)	(5.41)
Bandwidth Size	9.44	9.36	7.28
No. of observations	1,226	855	1,152
State and Year Fixed Effects	YES	YES	YES
Polynomial order of control function		Local Linear	
Bandwidth Type		Imbens-Kalyanaraman	

Notes: Standard errors are clustered at the constituency level and given in parentheses. Results displayed in each panel-column come from a separate regression that also controls for state and year fixed effects. In column (1) the Non-BIMAROU states include Arunachal-Pradesh, Assam, Goa, Gujarat, Haryana, Himachal Pradesh, Kerala, Maharashtra, Manipur, Meghalaya, Nagaland, Punjab, Tamil Nadu, Tripura and West Bengal. Column (2) includes Relatively Developed states as ranked by Raghuram Rajan Committee. They include Goa, Haryana, Kerala, Maharashtra, Punjab, Tamil Nadu, and Uttarakhand. Column (3) includes Low Corruption states as ranked by the Transparency International India (TII) on index of corruption. They include Kerala, Himachal Pradesh, Gujarat, Maharashtra, Punjab, West Bengal, Odisha and Uttar Pradesh.

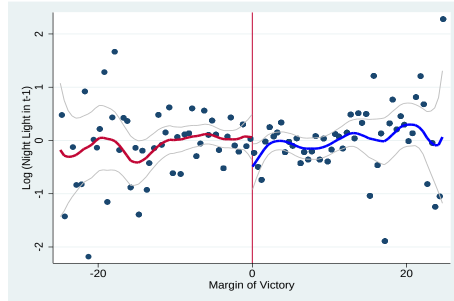
Asterisks denote significance levels (*=.10, **=.05, ***=.01)

Figure A-1

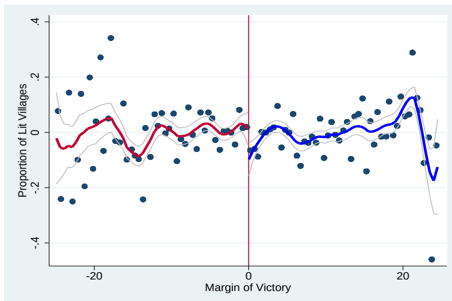
Alternate Dependent Variables: RD Effect and Balance Test



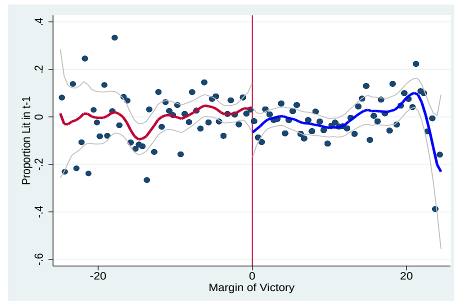
(a) RD Effect: Log (Night Lights)



(b) Log (Night Lights) t-1



(c) RD Effect: Prop of Lit Villages

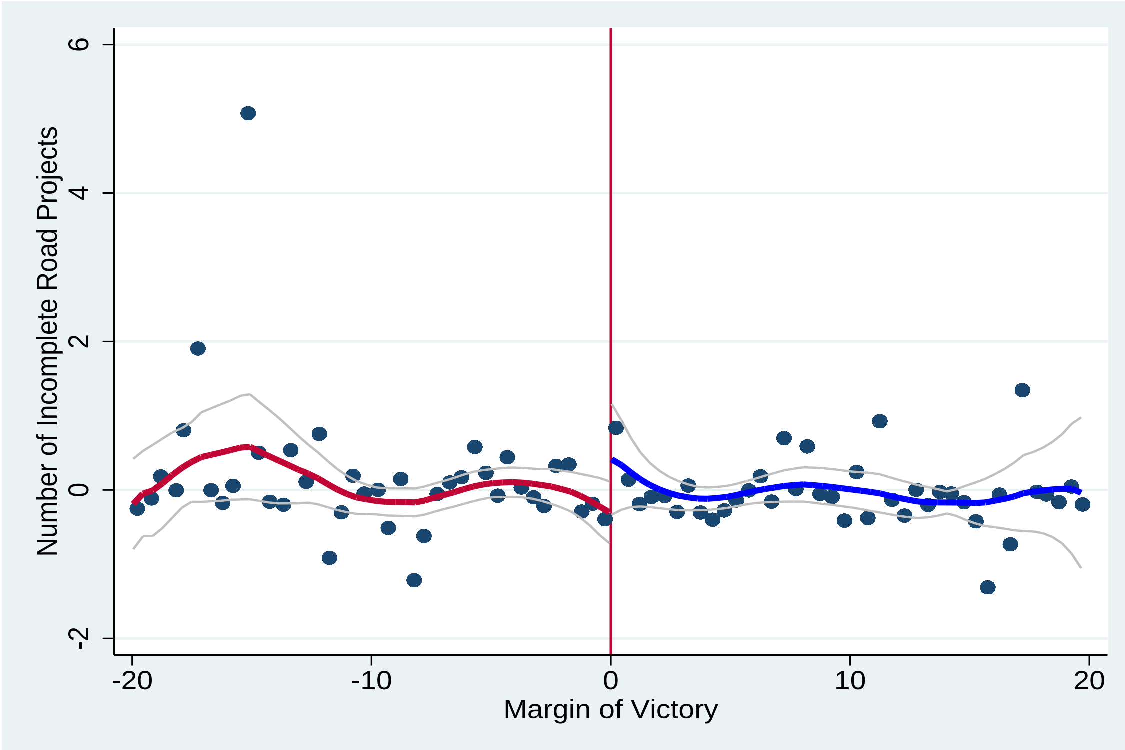


(d) Prop of Lit Villages t-1

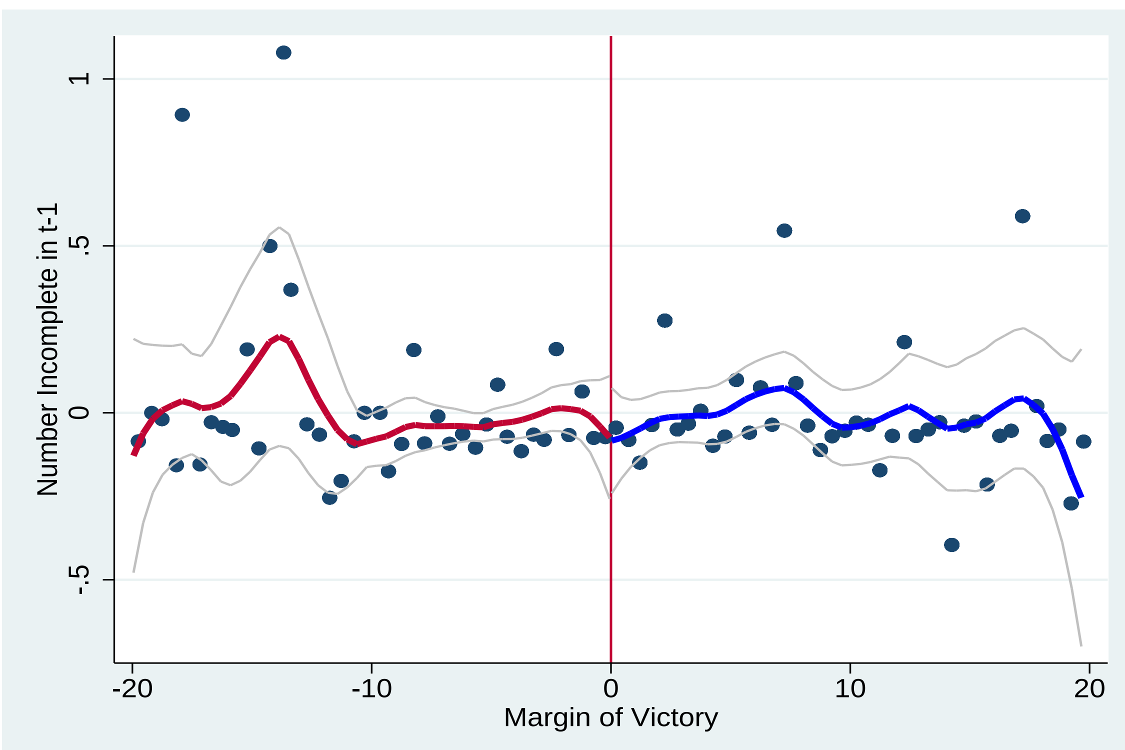
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. 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 triangular 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 A-2

Effect of Electing Criminally Accused Politicians on Number of Incomplete Road Projects



(a) RD Effect



(b) Balance Test

The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. The variable on the y-axis is number of incomplete road projects net of state and year fixed effects. The dots in the scatter plot depict the average number of incomplete road projects 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 triangular kernel and an optimal bandwidth calculator as suggested in Imbens and Kalyanaraman (2012). The confidence intervals are the 95% confidence intervals plotted using standard errors that are clustered at the constituency level.

Figure A-3
Share of Criminally Accused Candidates in India