Do Criminally Accused Politicians Affect Economic Outcomes? Evidence from India

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Abstract

We study the causal impact of electing criminally accused politicians to state legislative assemblies in India on the subsequent economic performance of their constituencies. Using data on the criminal background of candidates running in state assembly elections for the period 2004 – 2008 and a constituency-level measure of economic activity proxied by the intensity of night-time lights, we employ a regression discontinuity design and find that narrowly electing a criminally accused politician lowers the growth of the intensity of night-time lights by about 24 percentage points (approximately 2.4 percentage point lower GDP growth). The negative impact is more pronounced for legislators who are accused of serious or financial charges, have multiple accusations, are from a non-ruling party, have less than a college education, or have below median wealth. Overall, we find that the effect appears to be concentrated in the less developed and the more corrupt states. Similar findings emerge for the provision of public goods using data on India's major rural roads construction program.

JEL Classification: D72, D73, O40, O12

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

1 Introduction

Despite a 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. The share of Members of Parliament who face pending criminal charges has risen from 24 percent in 2004 to 34 percent in 2014 (NY Times 2014).[1] While the election of criminally accused candidates to public office is concerning in any context, this is especially true for India. Large quantities of funds are distributed by the government through a wide variety of interventions and programs, which have been plagued by costly scandals with estimated 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, resulting in an extremely slow judicial system.[3] Taken together, these realities create a context in which an influx of criminally accused politicians could be especially costly.

In this paper, we examine the *aggregate* economic costs of electing criminally accused politicians to State Legislative Assemblies (Vidhan Sabhas) in India for elections held during the 2004 to 2008 period. It is generally accepted, both in the literature and in public debate, that the election of criminally accused candidate is likely to have substantial economic costs for a constituency. Despite this widespread belief of an adverse effect, no formal estimates of the aggregate costs exist.[4] We take advantage of a Supreme Court of India order in 2003 which required all candidates seeking election to the Parliament of India or to State Legislative Assemblies to disclose information on their criminal background in a sworn affidavit submitted to the Election Commission of India (ECI). The

[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 marginal leakage of almost 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, subordinate and High Court seats are unfilled and 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.

[4] The existing literature finds negative economic effects but the aggregate effects are unclear. Nanda and Pareek (2019) find strong negative impacts on private sector investment ($765 million) but these are largely offset by increased public sector investment. Similarly, Chemin (2012) reports a close to 19 percent decrease in the monthly per capita expenditure of scheduled castes, scheduled tribes, or other backward classes. Since the effects on other segments of society are not estimated, the aggregate effects are unclear since the negative effects could be partially or entirely offset.

data from these affidavits not only allow us to identify criminally charged candidates, but also allow to differentiate candidates by the types and number of charges.

We measure constituency-level economic activity using satellite data on the intensity of night-time lights, since no GDP data are available for the state assembly constituencies. Night-time lights data have been used as a robust proxy for economic activity and measures of micro-development (Bleakley and Lin 2012, Henderson et al. 2012, Hodler and Raschky 2014, Michalopoulos and Papaioannou 2013, 2014, Pinkovskiy 2013, Storeygard 2016) at both the national and sub-national levels and offer several advantages.[5] First, unlike large household and economic surveys in India, night-time lights data are available at a highly disaggregated geographical level and can be aggregated to compile constituency-level measures. Second, these data are available annually, thus allowing for a more credible time series analysis. Third, night-time lights data are automatically collected by satellites and are therefore less prone to biases that may be present in administrative data.

An important challenge is 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) in certain constituencies. Therefore, constituencies that elect criminally accused candidates may not be comparable to those that elect non-accused candidates. We exploit a regression discontinuity design that credibly identifies the effect of electing criminally accused politicians by comparing constituencies that elect criminally accused with those that elect non-accused politicians in close elections. We find that electing a criminally accused politician has a large negative effect on economic activity in a constituency. On average, constituencies in which a criminally accused candidate barely wins experience roughly 24-percentage point lower yearly growth in the intensity of night-time lights as compared to those constituencies that barely elect a non-accused candidate. Moreover, these effects are larger for candidates accused of serious or financial criminal charges, or multiple criminal accusations. Furthermore, the timing of the negative effect is not instantaneous, but shows up after a lag. Using existing estimates from the literature on the elasticity of GDP growth to night-time lights growth, this is equivalent to roughly 2.4 percentage point lower GDP growth per year. We further find that the negative impact varies by state characteristics. In

[5]Pinkovskiy and Sala-i-Martin (2016) provides a literature review of the nighttime lights measure and propose a data-driven method to assess the relative quality of GDP per capita and survey means by comparing them to the evolution of satellite-recorded nighttime lights. Michalopoulos and Papaioannou (2013) cross-validate the satellite light density and regional development by examining the relationship between luminosity and economic performance using micro-level data from the Demographic and Health Surveys.

particular, the economic costs are more pronounced in states with high corruption levels, lower levels of development and plausibly weaker institutions (so-called 'BIMAROU' states). Finally, the effects are more pronounced in candidates from the ruling party, who have below median wealth (as proxied by assets), or who have below college education.

We find very similar effects using a proxy for public good provision: the roads built annually under the Pradhan Mantri Gram Sadak Yojana (PMGSY) program. The length (in kms) of roads built annually under the PMGSY is significantly lower in constituencies in which a criminally accused politician barely won compared to constituencies in which a non-accused barely won (we discuss this in Section 6). Overall, these results highlight the high aggregate economic costs of electing lower quality politicians (i.e. criminally accused) and point to likely significant individual costs in foregone access to public services.

Our paper contributes to several related literatures. Most narrowly, our findings contribute to the emerging literature on criminally accused politicians in India. 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, George at al., 2018). Others examine the selection of these candidates by political parties (Aidt et al. 2012, Tiwari 2014, Vaishnav 2011a, 2011b, 2011c). However, this growing body of literature on preferences over politician type and how to fight the selection of corrupt politician implicitly assumes that such politicians are less desirable for their constituencies. While studies point to economic costs in terms of investment, employment, and expenditure, the aggregate effects are unknown since these studies only focus on individual components of the local economy (Chemin 2012, Nanda and Pareek 2019).*Our study provides the first evidence of the aggregate economic cost of electing criminally accused politicians.* Since criminally accused politicians are not limited to India, our results may also be more broadly applicable [6]

Additionally, we contribute to the discussion regarding whether criminal accusations are 'too noisy' a signal to be useful for research or policy. In part, this concern arises since political rivals may have the incentive and means to fabricate charges against opponents. Similarly, there are

[6]While there are no studies on the prevalence of accused or criminal politicians, this is not unique to India. For instance, widespread criminality in politics is reported in Brazil (see: `http://www.law360.com/articles/457373/brazil-has-had-it-with-corporate-bribery`) and Pakistan (see: `http://www.dawn.com/news/1200870`). This is not limited to developing countries with both historical (e.g., political machines such as Tammany Hall in the US) and contemporary (e.g., the Mafia in southern Italy) examples in the developed countries.

examples of political activists being charged while participating in democratic protests (Jaffrelot and Verniers 2014). We find that accusations can provide useful information regarding politicians as the economic costs vary with the type and the number of criminal charges.[7]

We also make a modest contribution to the literature on the quality of politicians which typically uses proxies such as education (Alcantara 2008, Besley et al. 2005, De Paola and Scoppa 2010, Lahoti and Sahoo 2019, Martinez-Bravo 2017) and, more recently, personality (Callen et al. 2015). As our results demonstrate, whether or not a politician is criminally accused can have an important effect on the constituency level economic outcomes. Consequently, this may represent a pre-election indicator of candidate quality.

Finally, although our study focuses on India, it contributes to the broader understanding of the costs of electing lower quality politicians in clientelistic democracies. We find that the costs of electing criminally accused politicians are concentrated in states that are less developed and have higher levels of corruption. These findings are consistent with papers that suggest that low quality politicians (such as criminals) may provide targeted benefits to certain voters (Chandra 2004, Vaishnav 2011a, Banerjee and Pande 2007) based on certain salient factors, such as caste, ethnicity or class. Robinson and Verdier (2013) and van de Walle (2005) further suggest that less developed countries are associated with this type of clientelist or patronage politics. Bardhan and Mookherjee (2012) note that patronage democracies can lead to excessively short-term payoffs and a lack of long run investments, included the provision of public goods. In such democracies, criminally accused politicians may be especially detrimental for economic development and public goods delivery.

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 impact of electing criminally accused politicians on night-lights in Section 5. Section 6 presents variety of robustness checks and the paper concludes in Section 7.

[7] Using a field experiment in the context of the 2017 Uttar Pradesh state assembly elections, George at al., 2018 finds that voters respond to the content of the information provided – votes for candidates with severe charges drop by 7.7 percent and votes for candidates with no charges increase by 6.7 percent.

2 Background

2.1 Elected Representatives in India

India is a federal republic with a parliamentary system of government. The Parliament of India, the national level legislature, consists of two Houses: an Upper House (called the Rajya Sabha or the Council of States) and a Lower House (called the Lok Sabha or the House of the People). Those elected or nominated to either House of the Parliament are referred to as Members of Parliament (or MPs). State assemblies in India follow a similar structure with an Upper House called the Legislative Council (or Vidhan Parishad) and a Lower House 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) and are the focus of this paper. Similar to the national level, the election system at the state level is a "first-past-the-post" system and constituencies are divided into single member constituencies. The maximum length of an election term is constitutionally fixed at 5 years. Elections can occur before the constitutional stipulated length (e.g. when a coalition government suffers a loss in support from a partner).

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

2.2 Corruption and Criminality in Indian Politics

Elected officials are widely reputed to be engaged in corruption, mostly the 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 hundreds of billions of dollars.[8] Fisman et al. (2015) 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 the private sector opportunities available to political candidates. They find that the estimated annual growth rate of the winners' assets is 3-5 percent higher than those of the 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 their assets by 4-6 percent a year.[9] Asher and Novosad (2018) find that as local rents increase so too does the personal wealth of criminally accused politicians.

The issue of criminally accused candidates contesting elections in India is not new and has been debated at the highest level by the Election Commission of India, and the Indian Parliament. Even the Supreme Court of India showed serious concern regarding the increasing "criminalization" of politics, leading to its landmark 2003 judgment requiring candidates seeking election to the Parliament or to a Legislative Assembly to file sworn affidavits detailing their criminal convictions and charges (as well as their professional and educational qualifications, their assets and liabilities and those of their immediate family). Specifically, the affidavits require candidates to report prior convictions and any pending accusations for which the offense is punishable with imprisonment for two years or more, and in which a charge is framed or cognizance is taken by the Court of Law (that is, any criminal indictment). These charges are limited to those framed prior to the six-month period preceding the election. Since candidates face penalties for lying on the sworn affidavits and since rival candidates (and the media) have incentives to verify information contained in these affidavits, deliberate misreporting should be minimized.[10]

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

[9]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.

[10]These are sworn affidavits and there is a penalty for filing incorrect affidavit (e.g. disqualification, imprisonment for a term which may extend to six months, or a fine, or both). The affidavits can generally be accessed from the

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.[11] Surprisingly, the percentage of MPs facing criminal charges has increased between the 2009 and 2014 elections for the national Parliament. The findings are similar for the state assembly elections. According to the ADR report, over 30 percent of the MLAs currently face criminal cases.[12]

3 Regression Discontinuity Design

A key contribution of this paper is the casual identification of the effect of electing criminally accused politicians to state assemblies in India on a constituency level measure of economic activity. The main challenge is that the victory of criminally accused politicians is unlikely to be 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 provide 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.[13] In our setting, the assignment of treatment, whether a candidate is criminally accused or not ($ACCUSED$), 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, $ACCUSED = 1\ (MARGIN \geq 0)$, where 1(.) is the indicator function. The constituencies which fall below the cutoff ($MARGIN < 0$), the control group ($ACCUSED = 0$), elect a non-accused

ECI's website (http://eci.nic.in/eci/eci.html) and its website on candidate affidavit (http://eci.nic.in/eci_main1/LinktoAffidavits.aspx).

[11] An 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.

[12] 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. Unsurprisingly, following this success, an even greater number of criminally accused candidates (759) ran in the subsequent elections in 2012. Of these, 189 won seats in the state assembly (ADR, 2012a).

[13] The seminal paper by Lee (2008) exploits a regression discontinuity design using electoral data. Studies using a similar design in the context of India and elsewhere include Asher and Novosad (2017), Baskaran et al. (2019), Bhalotra et al. (2017), Bhalotra and Clots-Figueras (2014), Broockman (2014), Clots-Figueras (2011, 2012), Fisman et al. (2015), and Uppal (2009).

candidate who won against an accused runner-up, and the victory margin in these elections is the difference between 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 ($ACCUSED = 1$), 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. Crucially, nothing else varies discontinuously at the threshold. 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.

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:

$$GROWTH_{i,s,t+1} \quad = \quad \alpha + \gamma ACCUSED_{i,s,t} + f(MARGIN_{i,s,t}) + \mu_{i,s,t+1} \tag{1}$$

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

where $GROWTH_{i,s,t+1}$ is the yearly growth rate in night-time lights, our primary outcome of interest. This is measured as the difference in the natural log of night-time lights intensity for the constituency between the current and the previous period, for example [$Log(Y_{i,s,t+1})$-$Log(Y_{i,s,t})$], also widely accepted in the literature as a proxy for economic activity. *We do not include the night light measure for the year of election as it could be driven by the previous candidate in our specification.*[14]

The variable $ACCUSED_{i,s,t}$ 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. Finally $\mu_{i,s,t+1}$ is the error term. The coefficient of primary interest γ estimates the causal impact of electing criminally accused politicians to state assemblies in India on economic activity as proxied by the growth of night-time lights. The identification of this causal effect relies on fairly weak conditions on the conditional distribution of the error term μ, which is assumed to be a continuous function of the forcing variable ($MARGIN$).

[14]Previous versions of this study followed Henderson et al. (2012) and Chen and Nordhaus (2011) by including year fixed effects. The current versions reports year fixed effects for the main estimation result in our robustness tests. The results for the other tables are largely unchanged with the inclusion of fixed effects and are available upon request.

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.[15] Our preferred bandwidth specification follows the optimal bandwidth algorithm proposed by Imbens and Kalyanaraman (2012) [referred to as IK (h)]. 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-time lights is likely to be correlated over time within a constituency, the standard errors are clustered at the constituency level.

4 Data Description and Validity of the RD Design

4.1 Night-time Lights as a Measure of Economic Activity

To study the costs associated with electing criminally accused candidates, we need a measure 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.[16] Large surveys, such as the National Sample Survey, the India Human Development Survey, and the Economic Census of Firms are only available at the district level. These cannot be used for three reasons. First, the number of constituencies varies across districts and there is no logical way to weight constituencies within districts.[17] Second, even if a constituency level measure of economic activity could be derived, the above mentioned surveys are not available annually. Third, it is unclear how to implement a comparable RD using district level data and MLA level characteristics.

The satellite data are collected by the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) via a set of

[15]Different variations of equation (1) with different bandwidths and control function have been used in the literature. For example. Lee et al. (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 2019).

[16]Although we could in principle use the Census of India to look at various measures of public goods, it is only available for the years 2001 and 2011. Similarly, nationally representative household surveys (for e.g., National Sample Survey in India) are only available every 4-5 years. Therefore will not allow us to look at the annual change in outcome measures at the state assembly constituency level.

[17]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. Between the 2001 and 2011 Censuses, the number of districts increased from 593 to 640.

military weather satellites that have been orbiting the earth since 1970.[18] 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). *We compute the density of light by dividing the sum of light values from all of the pixels within the boundaries of each state assembly constituencies as defined by the Election Commission of India by the area of the constituency.*[19] *Thus, we aggregate night-time lights output to the state level assembly constituency to estimate economic costs of electing criminally accused politicians.*

Recent contributions by Henderson et al. (2012), Hodler and Rashky (2014), Michalopoulos and Papaioannou (2013, 2014), and Storeygard (2014) and previous work by Elvidge et al. (1997) find the use of night-time lights data as a useful proxy for development for regional analysis in countries with poor quality income data.[20,21] Results from Doll et al. (2006) and Pinkovskiy (2013) show that light density at night is a robust proxy of economic activity. More recently, Dhillon et al. (2017) uses the National Election Survey from 2004, which surveys voters at the parliamentary constituency level, to examine the correlation of standard economic indicators with night-lights in India. They find the correlation of night-lights with wealth to be about 0.6, while that with income and education lies between 0.4 and 0.45.[22] Overall, these studies find a strong within country relationship between GDP levels and night-time lights intensity and growth rates (see Pinkovskiy and Sala-i-Martin 2016 for an overview). Night-time lights data offer several advantages, most importantly that the pixels

[18]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.

[19]We use GIS data on administrative boundaries of states and assembly constituencies to enable the aggregation within each state assembly constituencies.

[20]Henderson et al. (2012) shows that night-time lights can also identify 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-time lights data are a useful proxy for economic activity at temporal and geographic scales for which traditional data sets are of poor quality or are unavailable (Henderson et al. 2012). Additionally, prior research shows that the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) can reliably detect electrified villages in developing countries and that the night lights output is a useful proxy for electricity provision (Doll et al. 2006, Min et al. 2013, Baskaran et al. 2015). Recent papers have used night-time 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).

[21]Michalopoulos and Papaioannou (2014) show that light density is correlated strongly with proxies of public goods including as access to electrification, the presence of a sewage system, access to piped water, and education and development. Min (2008) finds a strong association between access to electricity, public-goods provision and night light intensity for low income countries.

[22]A similar relationship holds at the district level in India (see Chaturvedi et al. 2011 and Bhandari and Roychowdhury 2011).

can easily be aggregated to the constituency level and that the availability of annual frequency allows for more detailed temporal analysis. Moreover, whether through increased electrification or higher incomes levels, it should arguably be related to local economic activity.

In the night-time lights data, 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). 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 without the top coded constituencies to verify their robustness. Another potential issue is blooming, which occurs when light from a brightly lit area spills over into neighboring areas. While this may be a concern around large cities, our sample is predominately rural.

Lastly, the levels of light output are relative brightness values. Since there is no onboard radiance calibration on the satellite sensors, there is no way to convert the relative brightness values to an actual level of illumination. This potentially complicates time series analysis because changes in the 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 or 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 robustness tests 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 key dependent variable is the yearly growth in the density of night-time lights. This is the difference in the natural log of night-time light intensity for the constituency between the periods $(t + 1)$ and (t). For ease of interpretation, we multiply the dependent variable by 100. As discussed earlier, this is widely accepted in the literature as a proxy for economic activity. Another advantage of specifying the dependent variable in this form is that it allows us to roughly calculate the impact on GDP using estimates from the literature on the elasticity of GDP growth to night-time lights growth. We also present results using three alternate dependent variables: the natural log of night-time lights, night-time lights in level, and the growth of night-time lights averaged over the entire election term.

We report the descriptive statistics of the key dependent variables in Table 1. The dependent variables are observed for each year of the election term, thus we observe about 4 observations for each included state level constituency.

Finally, we also use another outcome variable that is a proxy for public good provision at the constituency level (and an important determinant of growth in itself): the length of roads built under the PMGSY program (in kms). PMGSY is a fully centrally sponsored rural roads construction program launched in 2000 that aims to provide all weather road connectivity in rural areas, and forms an integral part of the Government of India's poverty reduction strategy. This program has been described as "unprecedented in its scale and scope" (Aggarwal 2018), connecting over 116,000 habitations with roads and another 23,000 currently under construction as of January 2016. 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. The administrative records of length of roads built under PMGSY are publicly available in the Online Management and Monitoring System (OMMS). We match roads data to the state assembly constituency level data to estimate the impact of electing criminally accused politicians on this measure of public good in Section 5.[23]

4.2 Election Results and Affidavit Data

We use the Election Commission of India (ECI) Statistical Reports on General Elections to State Legislative Assemblies for election data.[24] These reports provide important information related to elections, such as the name and code of the constituency, candidates and their vote shares, electorate size (number of registered voters), number who turned out to vote (number of voters), the candidate's gender and constituency type (whether reserved for SCs (STs) or non-reserved).[25] For criminal accusations, we rely on the data from sworn affidavits that we manually collected and

[23]The 2001 Census is the source for habitation-level data, which are collected by the PMGSY in order to determine the prioritization of roads.The PMGSY data are available at the census block level. Although there is no one-to-one matching between census blocks and state assembly constituencies (for example, a block can span more than one constituency), we match a block to a specific constituency if at least 50 percent of the villages in the block fell in that constituency.

[24]The reports are available at `http://eci.nic.in/eci_main1/ElectionStatistics.aspx`, accessed over the period from December 2017 till March 2019.

[25]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).

digitalized from the Election Commission of India. These data provide information on the number of criminal cases against each candidate, the charges associated with each criminal case, a classification of each accusation as serious or not, the asset and liabilities disclosures of each candidate and each candidate's level of education.

We consider all state elections held between 2004 and 2008. While the light data are available from 1992 onwards, we are limited by the data on affidavits, which became mandatory only after the Supreme Court order in 2003. Further, data are 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.[26] Also, the constituency boundaries changed in 2008 meaning constituencies before and after delimitation are not comparable.[27] Thus, between the Court order to file affidavits in 2003 and the redrawing of boundaries in 2008, we observe only 1 election per state. However, we utilize the night-lights data until 2012 for some states.[28]

Our main variable of interest is the accusation status of politicians.[29] 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 have been widely used to measure criminal accusations (Aidt et al. 2015, Asher and Novosad 2018, Banerjee et al. 2014, Fisman et al. 2014). There is some evidence to suggest that false cases are not as frequent as might be believed. Looking at a sub-sample of states, Vaishnav (2011a) finds that accusations are unrelated to prior electoral performance (a proxy for popularity),

[26]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 the growth of night lights or criminally accused candidates).

[27]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.

[28]The affidavits are available starting with the 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.

[29]It is not possible to examine convictions since there are only a handful of cases in which criminal proceedings reach a final verdict and the charges can stay pending for several years. 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.

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 the 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 criminally 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 (criminally 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-2 candidates represent each type (criminally accused and non-accused). 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 over two successive elections in each state, totaling over 3600 observations.[30]

While we are not the first study to use the data on criminal accusations, few studies, Vaishnav (2011a) 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, and whether it is related to any financial wrongdoing. Since any definition of serious criminal charges is inherently arbitrary, we rely on the classification used by the ADR which is based on such factors as the maximum punishment under the law, their violent nature, and offenses under the Prevention of Corruption Act.[31] Since ADR does not classify charges into financial and non-financial categories, we define a charge as financial if the corresponding IPC refers to a crime resulting in a loss to the

[30] 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. According to Lehne et al. (2018) the median number of candidates per state assembly election is eight, however only the top-2 candidates are competitive: the third placed candidates average 7% of the vote, the fourth placed candidates average 3%, the fifth 1.6% and the rest less than 1%.

[31] ADR compiles detailed data on each candidate's criminal cases and the type of charges framed in each case. It reports the exact criminal charge(s) for each candidate as defined under the Indian Penal Code (IPC). The 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 offense committed is of five years or more, or; (2) Whether the offense is non-bailable, or; (3) Offenses pertaining to the electoral violation (IPC 171E or bribery), or; (4) Offense related to the loss to exchequer, or; (5) Offenses the nature of which are related to assault, murder, kidnap, rape, or; (6) Offenses that are mentioned in Representation of the People Act, or; (7) Offenses under Prevention of Corruption Act, or; (8) Offenses 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/criteria-categorization-serious-criminal-cases`.

public exchequer.[32] 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, 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.

Table 2 provides the balance test on pre-determined constituency characteristics. Although some of the differences between the criminally accused and the non-accused are statistically significant in the top-2 mixed sample (i.e., one criminally accused against one non-accused), these become insignificant when we look at the sample of close elections within the 5% margin. Further, Figure A-7 depicts the distribution of criminally accused MLAs across Indian States.[33]

4.3 Event Study Plots

For a first impression of how the election of a criminally accused politician affects economic growth, we construct event study plots for the growth of night lights. Figure 1 plots the raw averages of growth of night lights for constituencies that elect a criminally accused politician in the election at time $t = 0$, and those constituencies which did not. The event study plot suggests that growth of night lights is roughly the same in the years preceding the election. In the year of the election, it is higher in constituencies that elect a criminally accused politician. Subsequent to the election, however, growth is noticeably slower in constituencies that elected a criminally accused politician. This suggests that the election of criminally accused politicians leads to lower growth. In the subsequent sections, we examine this more closely and provide a causal estimate of the effect.

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

[33] In our sample, approximately 53-percent of the winners report at least one criminal case, while 40-percent are facing at least one serious charge, and 19-percent at least one financial charge.

4.4 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 discontinuity at the cutoff in the density of the forcing 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 be more likely to win close elections. If this were the case, we would find a larger frequency of criminally accused candidates compared to non-accused candidates in the neighborhood of the cutoff. This would imply that the density of the margin of victory, the forcing variable, would show a discontinuity at the cutoff. Panels (a) – (b) of Figure 2 shows that the density of the victory margin above and below the cutoff is not statistically significant.

The second test of the validity of the RD design is whether the observed predetermined constituency characteristics are continuous around the cutoff. That is, while the characteristics for criminally accused and non-accused constituencies may be different over the entire sample, with the exception of the treatment, no other variable should be discontinuous around the cutoff. We formally check the continuity of various constituency characteristics in Figure 3. The dots in the scatter plot depict the averages over each successive 0.5% interval of the margin of victory. The curves are local linear regressions fit separately for positive and negative margins of victory using a triangular kernel and the optimal bandwidth calculator suggested by 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)–(c) of Figure 3, we compare criminally accused winners to non-accused winners on growth of night lights in the prior years (t-1, t-2, and t-3). In Panels (d)–(l) we compare the same on several other constituency characteristics: the electorate size, the number of voters, turnout, 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), MLA's incumbency status, winners gender, and runner-up gender, in the previous election. These results indicate that there are no statistically significant differences in the observed covariates around the cutoff. Therefore, the results from the McCrary test and the continuity of covariates strongly suggest that the assumptions underlying the RD design are valid in this setting.

5 Criminally Accused Politicians and Economic Activity

5.1 Main Results

We present the main results with a graphical illustration of the RD effect of electing criminally accused candidates in Figure 4 which plots the yearly growth of light density against the margin of victory for the criminally accused candidates.[34] The scatter plot shows the local averages of the growth of light density in each successive interval of 0.5 percent of margin of victory. The solid curves are plotted non-parametrically using a local linear regression with 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 vertical difference between the two curves at the cutoff (i.e. $MARGIN = 0$) reflects the estimated causal effect of electing a criminally accused candidate on the growth of light density. The RD figure shows a sharp drop in the growth of light density at the cutoff suggesting that constituencies that barely elect an accused candidate suffer a loss on average in economic activity over the election term compared to constituencies that barely elect a non-accused candidate.

Table 3 reports the point estimates of the RD effects. In column (1) we use a local linear regression with the optimal bandwidth (h) criterion proposed by Imbens and Kalyanaraman (IK). This is our main specification and is analogous to Figure 4. We find a statistically significant negative effect of electing criminally accused candidates: the annual growth of light density 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.[35] For robustness, we also present these results using alternate bandwidths in columns (2)–(4). In column (2), we use a bandwidth calculated using the Calonico, Cattaneo and Titiunik (CCT) (2014) algorithm, while in columns (3)–(4) we halve and double the IK bandwidth, respectively. The results in column (2) are quantitatively similar 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.

[34] The sample consists of elections in which, among the top-2 candidates, one is accused and the other is non-accused (see Section 4.2 for detailed discussion).

[35] In Table A-8 we estimate Table 3 with year fixed effects (in Column 2) and with state and year fixed effects (in Column 3) and find similar estimates.

Overall, the results remain statistically significant and similar in magnitude.

In Panel B of Table 3, we present the estimated effect on GDP growth, which is calculated by multiplying the estimated coefficient in the first row by the elasticity of night light to GDP growth.[36] The effect of electing a criminally accused candidate in our preferred specification lowers GDP growth by 2.4 percentage points.[37] Although the effect differs somewhat across the columns, these differences are not statistically different. Since growth during this period was roughly 7 percent, this implies a roughly 35 percent growth penalty (i.e., 2.4/7) from electing accused criminals.

5.2 Types and the Number of Charges

We next examine whether the costs of electing accused politicians vary with the underlying charges. If the economic costs associated with electing accused politicians are attributable to their criminality, the types of charges and the number of underlying cases should presumably matter. As noted in sub-section 4.2, we focus on two types of charges, serious, and financial (i.e. charges related to any loss to the public exchequer) charges.

Table 4 reports the results by the type of charges. In columns (1)–(4) of Panel A, we estimate the RD effect of electing candidates accused of financial charges on the yearly growth of light density. In particular, we compare constituencies with a winner with who has 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 accused of at least 1 crime but has no financial charges (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 accusations). We perform a similar analysis with serious charges in Panel B. We find consistent results: the type of charges matters. The estimated coefficients for both financial and serious crimes are consistently statistically significant whereas those for non-financial and non-serious charges are not. In particular, financial charges appear to be particularly important as the estimated coefficients (with the exception

[36] In the absence of constituency level measures of economic activity, we use Bickenbach et al.'s (2016) India specific estimate of the district level elasticity of night light to GDP growth, 0.10. Baskaran et al. (2019) report a similar elasticity, 0.12. Also see Pinkovskiy and Sala-i-Martin 2016 for an overview on the link between night-time lights data and GDP.

[37] This overall magnitude is similar to Baskaran et al. (2019) which estimates a 1.85 percentage point *increase* in GDP growth from narrowly electing a female MLA in India.

of column (4)) are noticeably larger than those estimated for any charge in column (1) of Table 3. Similar to Panel B of Table 3, we estimate the impact in terms of GDP growth in Panel C of Table 4.

In Table 5, we examine the effect of the number of criminal cases. A larger number of cases can be viewed as a "higher intensity treatment" and, insofar as there are costs to manufacturing and 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 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 negative effect. The estimated coefficients are consistently negative and statistically significant and greater than the effect for any charge [column (1) in Table 3].[38] Taken together, the results from Tables 4 and 5 demonstrate that the characteristics of the candidate, specifically the candidate's accusation record, underlie the earlier results and that the costs increase with the severity of the charge and number of the cases.

5.3 Mechanisms

We next consider why the election of criminally accused politicians might have such a strong impact on constituency growth. The handful of studies on the consequences of electing criminally accused politicians point to several underlying causes. As we describe in this section, our evidence is consistent these channels.

Most immediately, the election of criminally accused politicians strongly impacts local investment, employment, and expenditure per capita. Nanda and Pareek (2019) examine the impact of electing accused politicians on private firms. They find that the (narrow) election of an accused politician lowers private sector investment by $765 million USD over the duration of the term.[39] To put this in perspective, this represents a roughly 50 percent decrease in private sector investment relative to the mean. While this is partially mitigated by increases in public sector investment, the net effect on employment is clearly negative. Interestingly, this effect is not limited to investment as stock-returns for new projects announcements for firms in constituencies that narrowly elect accused

[38]We estimate similar models using the alternate thresholds of 2 and more financial (serious) charges, and 5 or more financial (serious) charges. The results are qualitatively similar to those in Table 5. The table is available upon request.

[39]This contrasts with the $561 million USD increase when a non-criminally accused politician is (narrowly) elected.

politicians similarly decrease. This suggests a strong belief that criminally accused politicians reduce the returns to investments for firms.

This belief finds support in Gehring et al. (forthcoming) and Asher and Novosad (2018). The former study finds that criminally accused politicians exhibit lower effort (than their non-accused politicians) in terms of attendance in parliament and in their utilization of local area development funds. In richer districts, however, these effects are muted which the authors argue reflect the rent seeking opportunities. In part, criminally accused politicians may make additional efforts to be re-elected (and therefore further extract rents). This does not, however, limit their nefarious activity as Asher and Novosad (2018) find that as local rents increase, criminally accused politicians are more likely to engage in more criminal behavior and to see their personal wealth increase. Taken together, this suggests that accused politicians engage in rent seeking behavior that leads firms to proactively reduce their investments.

However, the economic effects are not just limited to firms. Chemin (2012) finds that the (narrow) election of accused politicians also lowers the district per capita expenditure of SC/ST/OBC by 19 percent. In part, this may reflect the decreased employment reported by Nanda and Pareek (2019). Since roughly 65 percent of the population fits in these affected categories, this implies an overall decrease of per capita expenditure of roughly 12 percent.

The literature suggests three channels by which the election of accused candidates may affect economic outcomes. First, as shown above, there is a strong effect on the behavior of economic actors. Second, districts that elect a criminally accused MPs show strong increases in criminal activity (Chemin 2012), although it is not clear whether the election encourages criminality or whether they weaken the power of the state to fight crime. Lastly, the local political environment likely plays an important role. Nanda and Pareek (2019) finds that the negative effects of electing an accused politician decrease when she/he is affiliated with the ruling party. This may be due to more restrained behavior when there is oversight from the ruling party. Alternately, politicians affiliated with the ruling party may get more resources (Asher and Novosad, 2017). Similarly, they report that the effect only appears in states with above average levels of corruption.

Our own analysis supports the importance of the local political environment and suggests a new pathway via the delivery of public goods. We begin by considering different measures of the local political environment. 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 classifies as being "Least Developed" and "Relatively Developed".[40] 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.[41]

We present the results in Table 6. The RD estimate for BIMAROU states are reported in Panel (A), while Panel (B) reports the estimate for Least Developed states, and finally Panel (C) reports the estimate for High-Corruption states. These effects are negative and statistically significant. The magnitude of these coefficients are roughly two times larger than that of our main result [Table 3, column (1)]. [The coefficient is -24.33 for our baseline result (all states), -50.68 for BIMAROU states, -46.34 for Least Developed states, and -57.07 for High-Corruption states.] However, the results are statistically insignificant for Non-BIMAROU, and Relatively Developed states as shown in Table A-1. The estimated coefficients for the Low Corruption are statistically significant but smaller in magnitude than those of the High Corruption states.

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 certain states. One common feature of these states is the relatively weaker institutions whether judicial, police or political. 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 of lawless behavior and general impunity for politicians and bureaucrats (Cheng and Urpelainen, 2017). Thus, a criminally accused politician may be more able to compromise governance where institutions are weaker or less developed. Overall, these results confirm these findings from the literature.

In addition to the heterogeneity across states, there is also variation based on politician characteristics. Table 7 examines differences based on affiliation with the ruling party at the state level (in

[40] The Ministry of Finance classifies the following states as being "Least Developed": Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh and "Relatively Developed": Goa, Haryana, Kerala, Maharashtra, Punjab, Tamil Nadu, and Uttarakhand.

[41] TII classifies the following states as being "High Corruption": Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar and "Low-Corruption": Kerala, Himachal Pradesh, Gujarat, Maharashtra, Punjab, West Bengal, Odisha, and Uttar Pradesh.

Panel A), based on the declared wealth levels of the elected politician (in Panel B) and education levels (in Panel C). Similar to the findings in the literature, we find that the effect is concentrated in constituencies that elect accused politicians who are affiliated with the ruling party. This result is consistent with Asher and Novosad (2017). There is also evidence suggesting that wealth and education levels matter. While this may suggest "ability" plays a role, we are unable to distinguish from competing explanations.[42]

The literature discusses the apparent effects of rent-seeking behavior of accused politicians on local firms; we extend the literature to consider the delivery of public goods. While unstudied, the available evidence is suggestive. For instance, Lehne et al. (2018) find a 63-percent increase in the share of roads allocated to contractors who share the last name, and hence subcaste, of the electing politician.[43] We similarly focus on the construction of new roads from the PMSGY road building program. While we believe that this serves as a proxy for the general delivery of public goods, decreases in road provision should also directly affect economic growth.

We present the graphical illustration of the RD effect (and the balance test) of electing criminally accused candidates on the length of roads built annually in Figure 5 and the results from local linear regression for all states and by state characteristics in Table 8.[44] We report the results for all states in Panel A, BIMAROU states in Panel B, Least Developed states in Panel C, and High Corruption states in Panel D. While the overall effects are insignificant there are strong effects in the less developed and more backward states. [45] In addition, these states are less dependent than the BIMAROU or Least Developed states on federal transfers of funds.

Since these effects do no generalize across all states, they suggest that the effect of criminally accused politicians varies (as suggested by the earlier literature). Insofar as roads and, more broadly, the provision of public goods underpin local growth, this may also explain why the effects are particularly large in less development and more backward areas.

[42]For instance, time preferences are likely correlated with wealth and education levels. Less patient "criminals" might be more destructive.

[43]They advance two reasons to explain why a road would be listed as missing, both of which are indicative of corruption. Firstly, roads may be listed as completed without ever being built. Secondly, roads could be built with sub-standard materials leading to their complete or partial deterioration by the time of the 2011 census.

[44]We estimate the same for serious criminal charges in Table A-2 and financial charges in A-3.

[45]Surprisingly, we do not find negative impact of electing criminally accused politicians on roads construction for the high corruption states; this may be due to the smaller number of road projects approved and constructed in some of the high corruption states. States that have recorded the highest road construction are the BIMAROU and Least Developed states, for example Madhya Pradesh (63,548 km), followed by Rajasthan (58,462 km), Uttar Pradesh (45,905 km), Bihar (35,510 km) and Odisha (35,019 km).

5.4 Timing of the Negative Effects

We next examine whether the effect of electing accused politicians varies across the years of the term. That is, is the negative effect instantaneous (e.g., appears in the first year of the term) and then remains constant or rather does it accumulate over time?

In Table 9, we estimate the effect of elected an accused candidate separately for each year of the term. We also present the graphical illustration of the RD effect in Figure 6. The results show that the negative effect is not instantaneous. Rather, they accumulate over time. None of the estimated coefficients is significant in the first year. The estimated coefficients are statistically significant (but small in magnitude) in the second year and generally loose their statistical significance in the third year. However, by the last year, the estimated effects are very large in magnitude. This suggests that the election of criminally accused politicians does not instantaneously result in lower economic activity and that the economic costs show up after a lag. 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.

6 Robustness

In this section, we perform further robustness checks using alternate functional forms and 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 extreme values.

6.1 Sensitivity Analysis of RD Specification

While earlier researchers emphasized the analysis of different bandwidths (Imbens and Lemieux 2008), recent studies broaden the focus to include alternate control functions (Dell 2010, Lee and Lemieux 2009, Meyersson 2014). We address this in Table A-4 which reports the RD effects for linear, quadratic, cubic, and quartic functions using the IK (h), CCT, h/2, and 2h bandwidth choices.[46]

[46] 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.

Variations in the polynomial order in the control function are ordered by row and bandwidth choices by column in this table.

In general, we find that the RD estimates are negative and statistically significant and qualitatively similar to the effect estimated in Table 3. Statistical significance, however, is lost at higher bandwidths and/or with larger order polynomials of the control function.

6.2 Alternate Dependent Variables

Since night-time lights and their distribution can be measured in several ways, we explore three alternate definitions of the dependent variable: the intensity of night lights in logs, in levels, and the growth of night-time lights averaged over the election term of the candidate. We present the estimates of the RD effect for the three dependent variables in Table A-5.

While we focus on the yearly growth of night-time lights (for better comparison across constituencies), both growth rates and levels are used when researchers talk about growth. Results from Table A-6, columns (1)–(3) suggest that the point estimates remain statistically significant and negative using the alternate definitions of the dependent variable.

It is important to note that there was rapid economic growth and increased electrification during this period, and tremendous growth in the intensity of night lights. Some rural constituencies, particularly those with initially low levels of night lights, experienced very high growth of night light levels.

6.3 Extreme Values

As previously noted, the night-time lights data are 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 where we cannot observe any changes above an intensity of 63. Although this is unlikely to be systematically correlated with the accusation status of elected candidates, we directly address this in Table A-6. In our RD sample, there are 63 fully lit constituencies. 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 main results.

Another concern is the presence of zeros in some constituencies where the light output is too low to be picked up by the satellites, which raises issues while calculating growth rates and could cause large swings in their values. In Panel A of Table A-7, we explicitly consider the role of extreme values by trimming the sample of observations which are more than 3 standard deviations from the mean. The effect, albeit smaller, is generally significant indicating that our results are robust to the extreme values. In Panel B, we drop observations with a 0 in either t or t-1 (election year or the year preceding the election, both of which could result in large swings when calculating the annual growth rate). The results are again consistent with our main results.

6.4 Controlling for Covariates

In an RD framework, it is not necessary to control for various pre-determined covariates as the treatment is independent of these covariates at the cutoff. However, it is possible to directly control for the covariates and estimate the local linear RD regression. We present the RD results in Table A-8.

We present the RD regression result without any fixed effects in column (1), with only year fixed effects in column (2), with year and state fixed effects in column (3), and finally in addition to state and year fixed effects we add lagged growth of night lights (t-1), and characteristics from the previous election: whether the winner was an incumbent, the electoral size, the numbers of voters, total turnout, whether the winner was aligned with the ruling part in the state, the gender of the winner and the runner-up, and whether the constituency was reserved for SC or ST in column (4).

Overall, our results remain similar to our main findings in Table 3. This provides further reassurance about the validity of the RD design in our context.

7 Conclusions

In this paper, we estimate the aggregate economic costs of electing criminally accused politicians at the constituency level using data on the intensity of night-time lights and the sworn affidavits of candidates on their criminal background. We find several important results. We find a large negative and causal impact as the yearly growth of the intensity of night lights is roughly 24-percentage point lower for constituencies that barely elect a criminally accused candidate as compared with those that do not. The estimated effect is not just statistically significant but it is also economically meaningful;

this effect translates into roughly a 2.4-percentage point lower GDP growth per year. While we only have aggregate constituency level outcomes, this forgone growth must also impact poverty reduction and other micro-level development outcomes.

Using data on the specific charges (e.g. serious or financial criminal charge vs. any criminal charge) we find large variation in the impact of electing accused politicians on the intensity of night-time lights. In contrast, the election of candidates with only non-serious or non-financial charges has no impact on the subsequent growth. Additionally, this effect increases with the number of underlying criminal cases, which may serve as an indicator of 'intensity of treatment'. This variation not only highlights the importance of the precise accusations but also more reliably captures the potential criminality of politicians. This possibility is further underlined by the gradual accumulation of the costs over time.

We further examine how the impact of electing criminally accused candidates varies across state characteristics. We find that the costs are more pronounced in states with high corruption levels, lower levels of development and those which plausibly have weaker institutions ('BIMAROU' states). This suggests that the local context may mitigate the detrimental effect of electing lower quality politicians, such as accused politicians. While we cannot identify the precise channels, we believe that institutions can play an important role in constraining the actions of elected politicians. Additionally, in the spirit of Kremer's 'O-Ring' theory (1993), local growth might depend on several complementary pieces including effective leadership. In certain contexts, such as less developed areas, there is no redundancy in leadership making the effects of inferior politicians more detrimental. The heterogeneity analysis by candidate characteristics suggests that the negative impact is more pronounced amongst candidates from the ruling party, who have below median wealth (proxied by assets), and have below college education. The later two may be proxies for "ability".

Finally, using data on roads construction – a commonly used measure of public goods provision in developing countries – we find a large negative impact of criminally accused on the length of roads built under PMGSY. This negative effect varies by state characteristics and is largely driven by 'BIMAROU' and 'Least Developed' states.

We interpret our key dependent variable as a measure of economic activity, but it may also proxy for access to electricity. Taken together, roads construction and access to electricity are arguably some of the most important public goods in India, thus the negative impact we estimate is likely to have important welfare consequences. Consequently, the election of accused politicians and, more generally, of lower quality politicians may have adverse effects along a variety of dimensions.

More broadly, our results are consistent with the literature on patronage democracies. One manifestation of a patronage democracy is the election of politicians who are able and willing to provide targeted benefits (Burgess et al. 2015). These benefits could be targeted based on caste as in India (Chandra 2004), class, or ethnicity in other contexts. Therefore, instead of focusing on the overall outcomes (such as the delivery of public goods), voters focus on whether politicians can deliver targeted transfers to their specific group or caste. Not only are voters perhaps more likely to overlook accusations but these accusations might serve as a signal of the politician's willingness to use the office to reward fellow-group members (Chauchard 2014, Wade 1985). If true, our results suggest three consequences. First, this can result in the election of criminally accused candidates, and therefore potentially explain the ever increasing number of accused politicians who are elected in India. Second, the election of lower quality candidates in patronage democracies leads to lower aggregate growth. Third, these effects, however, are mediated by the local context (especially the institutional and legal context). In the more developed, and less corrupt states in our sample, the effects of the accused politicians were lower, perhaps due to the strength of institutions.

Although we study a particular context, lower quality politicians are believed to be pervasive in many developing countries. While the underlying cause is often context-specific and may range from caste-politics to tribal and ethnic voting, we believe that our analysis is suggestive for other contexts.

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TABLE 1

Descriptive Statistics for Dependent Variables

	Full Sample					**Top-2 Mixed Sample**				
	N	Mean	Std. Dev	Min	Max	N	Mean	Std. Dev	Min	Max
Growth of Light Density (%)	10154	3.18	96.5	-1003.5	1030.7	3529	2.71	82.0	-1003.5	1030.7
Log Light Density	12785	10.7	2.32	0	13.7	4445	11.1	1.75	0	13.7
Road Length (kms)	3512	21.3	22.3	0.10	315.1	1256	20.0	19.7	0.40	181.2
Growth of in (t-1)	2631	24.0	116.4	-900.6	980.6	916	19.2	101.9	-487.6	847.4
Log Light in (t-1)	2631	10.5	2.23	0	13.7	916	10.9	1.59	0	13.7
Road Length (kms) in (t-1)	1090	11.4	22.9	0.50	636.5	416	9.23	9.13	0.60	88.0
Log Electorate Size in (t-1)	2633	11.8	0.81	8.22	13.8	918	12.0	0.47	9.29	13.6
Log Number Voted in (t-1)	2633	11.3	0.73	8.03	13.0	918	11.6	0.43	8.86	13.0
Turnout in (t-1)	2633	66.3	12.0	17.0	99.9	918	64.3	11.0	17.0	93.9
SC Reserved	2633	0.14	0.35	0	1	918	0.12	0.33	0	1
ST Reserved	2633	0.12	0.33	0	1	918	0.052	0.22	0	1
Ruling Party in (t-1)	2633	0.57	0.49	0	1	918	0.54	0.50	0	1
Incumbent in (t-1)	2633	0.39	0.49	0	1	918	0.40	0.49	0	1
Winner's Gender in (t-1)	2633	0.063	0.24	0	1	918	0.064	0.25	0	1
Runner-up's Gender in (t-1)	2633	0.063	0.24	0	1	918	0.059	0.24	0	1

NOTES: Full sample includes candidates irrespective whether one of the top 2 is a criminally accused or not. Top-2 mixed sample includes candidates with 1 criminally accused against 1 non-accused in the top 2.

TABLE 2

Balance Test on Pre-determined Characteristics

	Top-2 Mixed Sample			**Top-2 Mixed Sample within 5% margin**		
	Criminal	Non-Criminal	Diff.	Criminal	Non-Criminal	Diff.
Growth of Light in (t-1)	21.988	33.736	-11.748**	26.037	24.503	1.534
	(110.02)	(142.45)	(5.98)	(89.16)	(110.66)	(11.39)
Log Light in (t-1)	10.467	10.788	-0.321***	10.7	10.937	-0.237
	(2.33)	(1.65)	(0.12)	(1.40)	(1.41)	(0.16)
Road Length (kms) in (t-1)	11.915	9.52	2.395	8.178	9.777	-1.599
	(25.06)	(10.54)	(1.74)	(6.52)	(9.94)	(1.35)
Log Electorate Size in (t-1)	11.7	12.065	-0.364***	12.085	12.079	0.005
	(0.85)	(0.41)	(0.04)	(0.44)	(0.39)	(0.05)
Log Number Voted in (t-1)	11.277	11.61	-0.332***	11.608	11.617	-0.009
	(0.78)	(0.37)	(0.04)	(0.37)	(0.36)	(0.04)
Turnout in (t-1)	66.665	64.496	2.169***	63.042	64.043	-1.002
	(12.11)	(11.13)	(0.61)	(10.35)	(11.12)	(1.22)
SC Reserved	0.142	0.126	0.016	0.12	0.072	0.048
	(0.35)	(0.33)	(0.02)	(0.33)	(0.26)	(0.03)
ST Reserved	0.136	0.05	0.086***	0.032	0.026	0.005
	(0.34)	(0.22)	(0.02)	(0.18)	(0.16)	(0.02)
Ruling Party in (t-1)	0.572	0.576	-0.004	0.475	0.526	-0.052
	(0.50)	(0.50)	(0.03)	(0.50)	(0.50)	(0.06)
Incumbent in (t-1)	0.376	0.439	-0.063**	0.354	0.375	-0.021
	(0.48)	(0.50)	(0.03)	(0.48)	(0.49)	(0.06)
Winner's Gender in (t-1)	0.065	0.057	0.008	0.07	0.072	-0.003
	(0.25)	(0.23)	(0.01)	(0.26)	(0.26)	(0.03)
Runner-up's Gender in (t-1)	0.067	0.048	0.019	0.051	0.046	0.005
	(0.25)	(0.21)	(0.01)	(0.22)	(0.21)	(0.02)

NOTES: Top-2 mixed sample includes candidates with 1 criminally accused against 1 non-accused in the top 2. Columns (3) and (6) have standard errors of the difference in the means of accused and non-accused MLAs in the parentheses. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 3

Effect of Electing Criminally Accused Politicians on Growth of Night Lights

	Panel A			
Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
Criminally Accused	-24.33**	-20.46**	-28.36*	-14.75**
	(10.23)	(8.42)	(15.52)	(6.30)
Bandwidth Size	6.16	8.37	3.08	12.32
No. of observations	1,513	1,850	744	2,429
Bandwidth Type	IK (h)	CCT	h/2	2h
Polynomial order of control function	Local Linear			
	Panel B			
	Estimated Percentage Change in GDP			
Bichenbach et al. (2016) India-specific elasticity (0.10)	-2.9	-2.5	-3.4	-1.8

NOTES: Standard errors are clustered at the constituency level and given in parentheses. In Panel A, 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 in a top-2 mixed race. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. In Panel B, we use India specific elasticity of 0.10 to convert the growth in lights into GDP growth. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 4

Effect of Electing Criminally Accused Politicians by Accusation Type

	PANEL A							
Dependent Variable	**Growth of Night Lights**							
Type of Accusation	Financial Charge				Non-Financial Charge			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Linear	-43.84**	-39.25**	-52.01**	-26.29**	-12.19	-11.28	-18.25	-5.76
	(18.77)	(17.34)	(26.29)	(12.20)	(8.91)	(8.12)	(15.51)	(5.27)
Bandwidth Size	8.04	9.00	4.02	16.08	8.59	9.61	4.30	17.19
No. of observations	519	579	278	867	1,312	1,445	736	2,000
	PANEL B							
Type of Accusation	Serious Charge				Non-Serious Charge			
Local Linear	-25.98***	-24.50***	-20.31*	-15.09**	-15.28	-13.95	-22.59	-11.49
	(9.82)	(8.87)	(11.65)	(6.83)	(14.18)	(11.64)	(28.27)	(8.43)
Bandwidth Size	5.94	7.26	2.97	11.89	12.72	16.05	6.36	25.44
No. of observations	1,016	1,141	511	1,576	809	893	473	1,051
Bandwidth Type	IK (h)	CCT	h/2	2h	IK (h)	CCT	h/2	2h
	PANEL C							
	Estimated Percentage Change in GDP							
	Financial Charge				Non-Financial Charge			
Bichenbach et al. (2016) Indian-specific elasticity (0.10)	-4.4	-3.9	-5.2	-2.6	-1.2	-1.1	-1.8	-0.6
	Serious Charge				Non-Serious Charge			
Bichenbach et al. (2016) India-specific elasticity (0.10)	-2.6	-2.5	-2.0	-1.5	-1.5	-1.4	-2.3	-1.1

NOTES: Standard errors are clustered at the constituency level and given in parentheses. 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. The RD estimates in columns (1)–(8) are on a local linear regression using a triangular kernel. In Panel C, we use India specific elasticity of 0.10 to convert the growth in lights into GDP change. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 5

Effect of Electing Criminally Accused Politicians by Multiple Cases

Dependent Variable	**Growth of Night Lights**							
Type of Accusation	Multiple Cases (>= 2)				Multiple Cases (>= 5)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Linear	-32.10***	-27.99**	-32.84**	-19.67**	-66.47**	-58.31**	-90.15**	-43.39**
	(12.30)	(11.33)	(15.86)	(8.36)	(27.09)	(25.25)	(36.57)	(18.88)
Bandwidth Size	7.05	8.36	3.52	14.09	7.29	8.71	3.65	14.58
No. of observations	770	870	393	1,193	214	233	106	306
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. 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. The RD estimates in columns (1)–(8) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 6

Effect of Electing Criminally Accused Politicians by State Characteristics

Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
	PANEL A: BIMAROU States			
Criminally Accused	-50.68**	-37.67**	-47.52	-29.52**
	(22.49)	(17.18)	(30.52)	(14.44)
Bandwidth Size	4.90	7.43	2.45	9.80
No. of observations	472	680	269	825
	PANEL B: Least Developed States			
Criminally Accused	-46.34**	-38.95**	-51.37*	-25.59*
	(21.08)	(18.26)	(30.19)	(13.36)
Bandwidth Size	5.92	7.48	2.96	11.83
No. of observations	567	678	308	894
	PANEL C: High Corruption States			
Criminally Accused	-57.07**	-53.23**	-68.34	-36.78**
	(28.57)	(25.59)	(44.57)	(18.08)
Bandwidth Size	6.09	7.53	3.05	12.19
No. of observations	432	482	210	691
Bandwidth Type	IK (h)	CCT	h/2	2h
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 from a separate regression. 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. Panel A includes the BIMAROU states: Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh, and Uttarakhand; Panel B includes the Least Developed states as ranked by Ministry of Finance: Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh; and Panel C includes the High Corruption states as ranked by Transparency International India (TII) on index of corruption: Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 7

Effect of Electing Criminally Accused Politicians by Candidate Characteristics

Dependent Variable	**Growth of Night Lights**							
	PANEL A							
	Ruling Party				Non-Ruling Party			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criminally Accused	1.81	0.73	-0.78	2.91	-50.79**	-43.42**	-50.43	-36.92***
	(6.31)	(7.48)	(9.98)	(4.51)	(21.95)	(17.00)	(31.24)	(14.07)
Bandwidth Size	10.54	8.04	5.27	21.09	5.25	8.10	2.63	10.50
No. of observations	1,167	954	662	1,726	632	838	325	1,016
	PANEL B							
	Above Median Wealth				Below Median Wealth			
Criminally Accused	-11.01	-10.48	-18.15	-7.89	-33.51**	-29.56**	-29.04	-19.92**
	(9.12)	(7.53)	(15.83)	(5.82)	(14.61)	(12.50)	(17.96)	(9.58)
Bandwidth Size	11.21	14.5	5.6	22.42	5.93	7.75	2.97	11.87
No. of observations	1,154	1,314	698	1,570	731	870	379	1,151
	PANEL C							
	College Educated				Below College Educated			
Criminally Accused	-20.86	-18.55	-26.65	-11.64	-19.39*	-22.04*	-32.23*	-12.64*
	(13.33)	(11.42)	(21.21)	(8.21)	(10.36)	(11.93)	(16.93)	(7.14)
Bandwidth Size	6.61	8.54	3.31	13.22	10.30	8.61	5.15	20.59
No. of observations	887	1,041	440	1,384	961	821	554	1,409
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. Results displayed in each column come from a separate regression. 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. In Panel A, columns (1)–(4) is for candidates from the ruling party, and columns (5)–(8) is from the non-ruling party. In Panel B, columns (1)–(4) is for candidates with below median wealth as reported in their affidavits, and columns (5)–(8) is for the above median wealth. In Panel C, columns (1)–(4) is for candidates with college education as reported in their affidavits, and columns (5)–(8) is for the below college education. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 8

Effect of Electing Criminally Accused Politicians on Roads Built Annually (in kms)

Dependent Variable	**Length of Roads Built (in kms)**			
	(1)	(2)	(3)	(4)
	PANEL A: All States			
Criminally Accused	-6.7	-6.75	-2.05	-3.39
	(4.43)	(4.51)	(5.35)	(3.19)
Bandwidth Size	7.92	7.45	3.96	15.84
No. of observations	541	994	289	810
	PANEL B: BIMAROU States			
Criminally Accused	-16.52**	-16.74**	-11.21	-12.89**
	(7.71)	(7.89)	(8.59)	(5.58)
Bandwidth Size	7.59	7.01	3.79	15.17
No. of observations	254	422	141	368
	PANEL C: Least Developed States			
Criminally Accused	-17.37**	-17.24**	-13.25	-10.33**
	(7.36)	(7.82)	(9.03)	(5.12)
Bandwidth Size	8.79	7.6	4.4	17.59
No. of observations	296	436	155	394
	PANEL D: High Corruption States			
Criminally Accused	1.11	2.94	2.89	4.38
	(7.29)	(10.66)	(10.68)	(5.13)
Bandwidth Size	8.37	4.2	4.18	16.74
No. of observations	158	266	82	226
Bandwidth Type	IK (h)	CCT	h/2	2h
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 from a separate regression. 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. Panel A includes all the states; Panel B includes the BIMAROU states: Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh, and Uttarakhand; Panel C includes the Least Developed states as ranked by Ministry of Finance: Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh; and Panel D includes the High Corruption states as ranked by Transparency International India (TII) on index of corruption: Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE 9

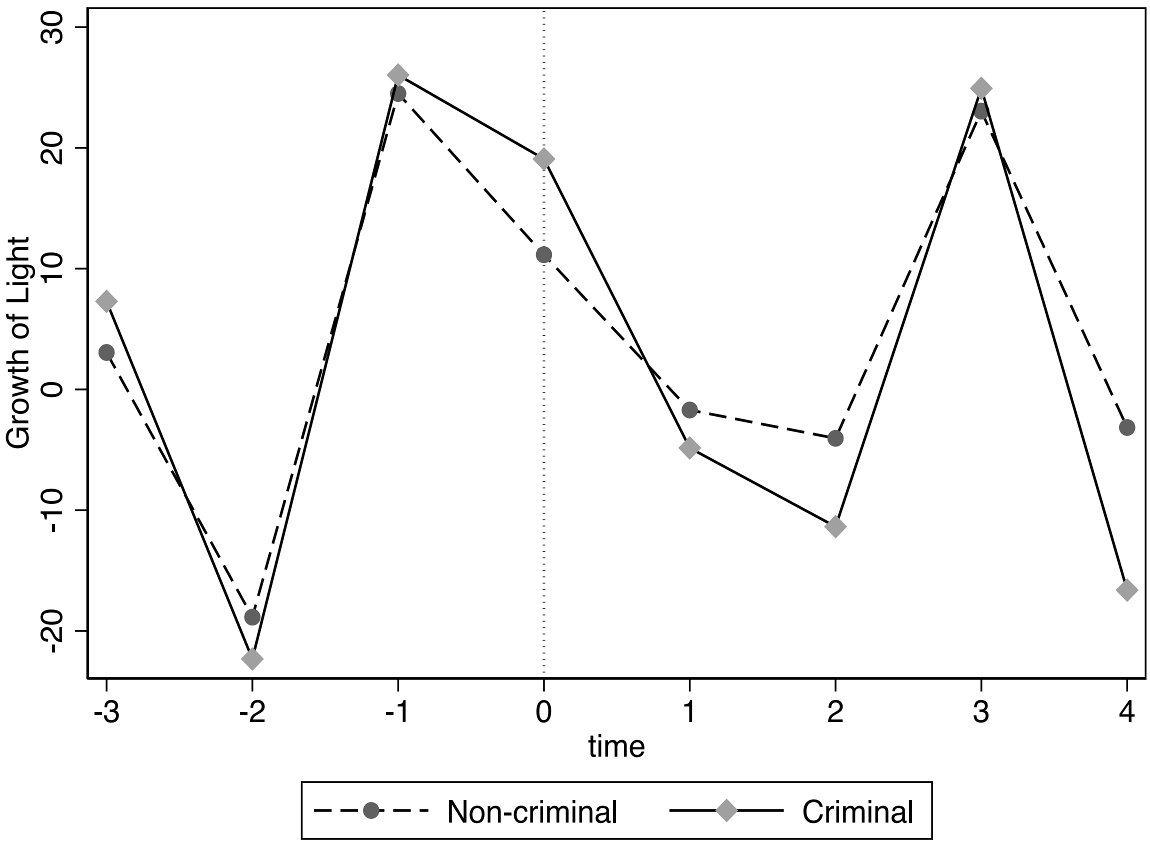
Effect of Electing Criminally Accused Politicians by Year in Power

Dependent Variable	$Log(Y_{ist+1}) - Log(Y_{ist})$				$Log(Y_{ist+2}) - Log(Y_{ist})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					PANEL A			
Criminally Accused	-7.7	-8.96	-1.45	-8.05	-23.05*	-23.46*	-21.08	-18.08*
	(9.86)	(9.86)	(14.61)	(6.32)	(13.12)	(12.75)	(18.25)	(9.33)
Bandwidth Size	7.71	8.64	3.85	15.42	8.88	9.54	4.44	17.75
No. of observations	446	483	243	707	493	520	268	750
Dependent Variable	$Log(Y_{ist+3}) - Log(Y_{ist})$				$Log(Y_{ist+4}) - Log(Y_{ist})$			
					PANEL B			
Criminally Accused	-49.88*	-38.37	-46.04	-29.71	-111.48**	-81.85**	-124.74*	-69.26**
	(30.14)	(23.79)	(35.78)	(19.82)	(47.19)	(33.91)	(68.81)	(29.26)
Bandwidth Size	5.54	8.52	2.77	11.07	5.54	9.16	2.77	11.08
No. of observations	348	472	170	569	317	459	150	522
Bandwidth Type	IK (h)	CCT	h/2	2h	IK (h)	CCT	h/2	2h
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 from a separate regression. 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 columns (1)–(8) are based on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

Figure 1

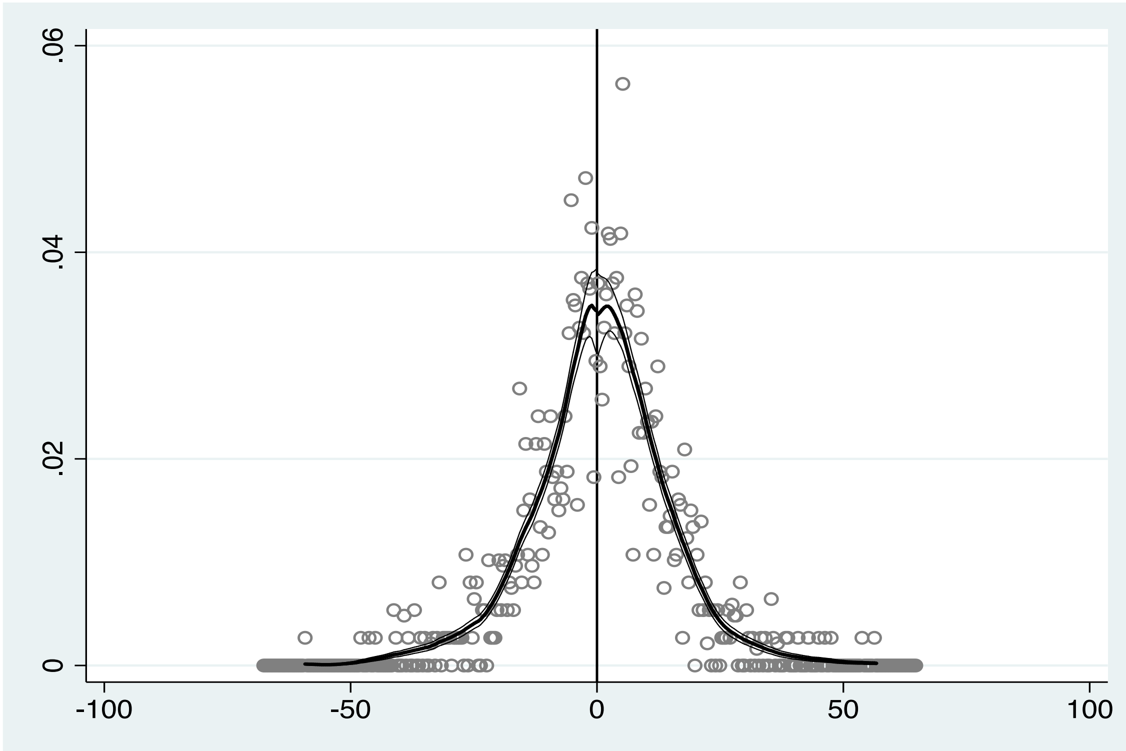
Event Study: Effect of Electing Criminally Accused Politicians on Growth of Night Lights



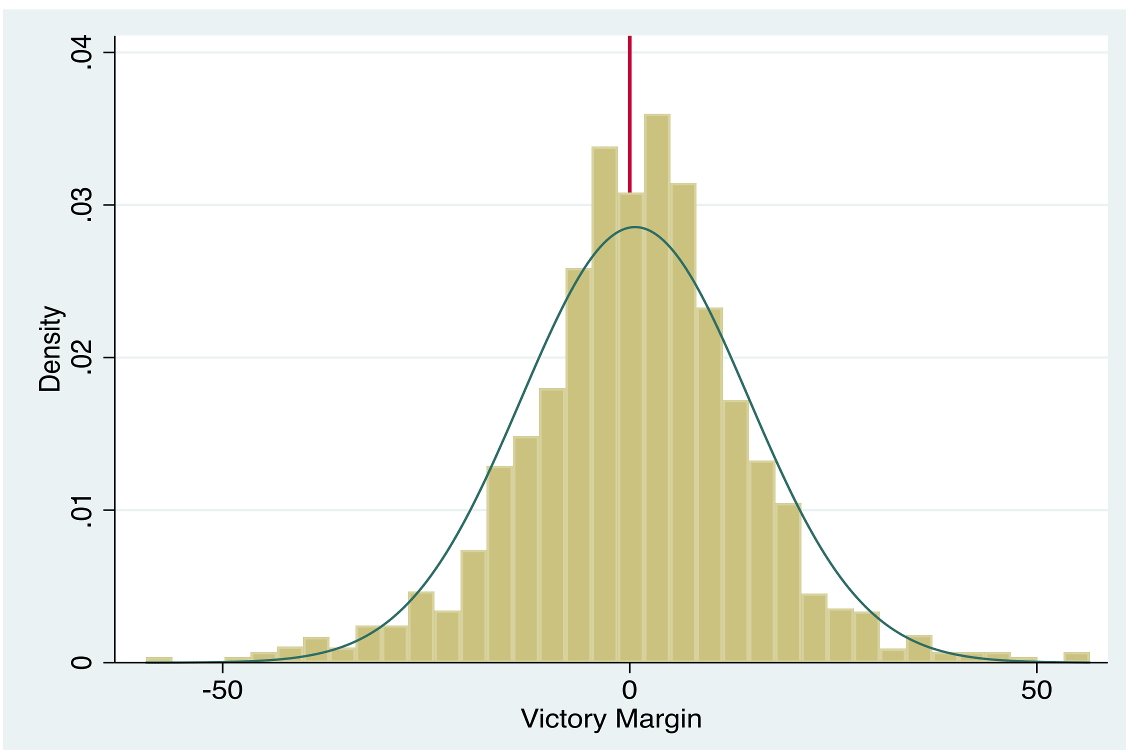
Each line plot represents the raw averages of the growth of light density for that year in relation to t=0, which is the year of the election.

Figure 2

Continuity of the Victory Margin between Criminally Accused and Non-Accused



(a) McCrary Test

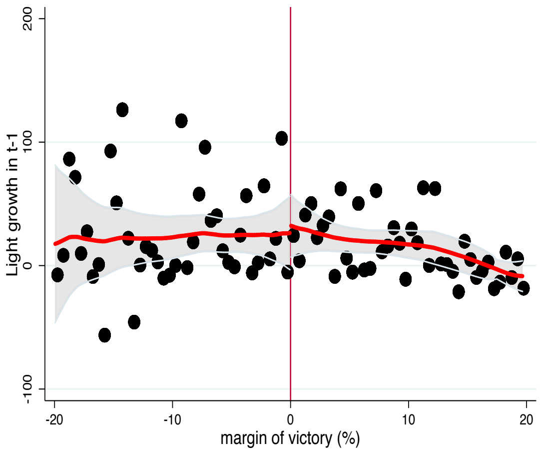


(b) Density of the Victory Margin

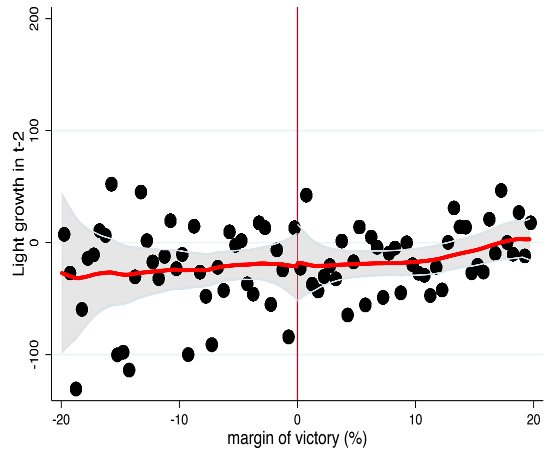
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up. The estimated size of discontinuity in margin of victory (log difference in height) is -0.041 (se $= 0.089$).

Figure 3

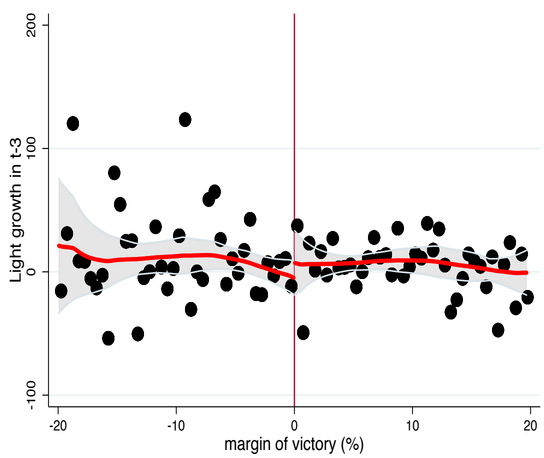
Balance Test for Constituency Characteristics



(a) Growth of Light in t-1



(b) Growth of Light in t-2

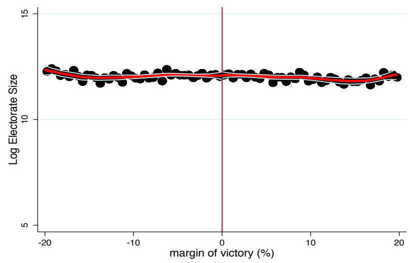


(c) Growth of Light in t-3

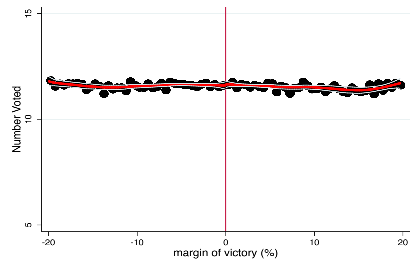
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up.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

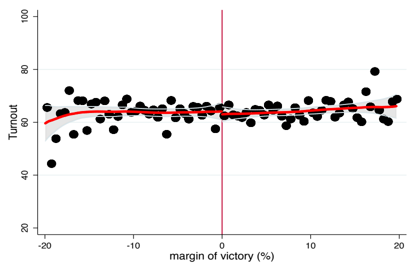
Balance Test for Constituency Characteristics



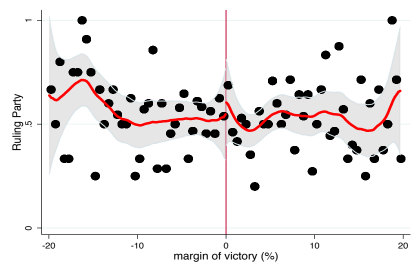
(d) Electorate Size in t-1



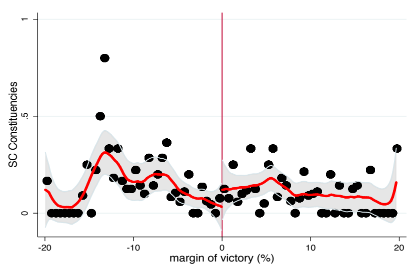
(e) Number Voted in t-1



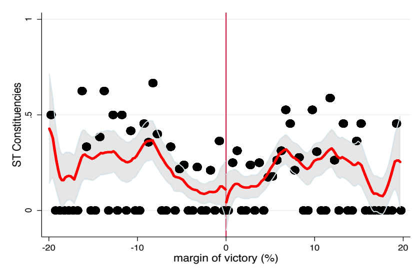
(f) Turnout in t-1



(g) Ruling Party in t-1



(h) SC Constituencies

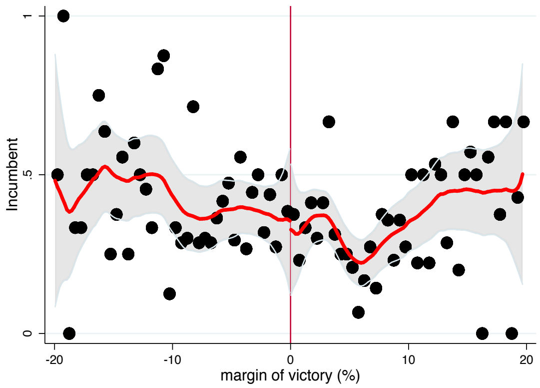


(i) ST Constituencies

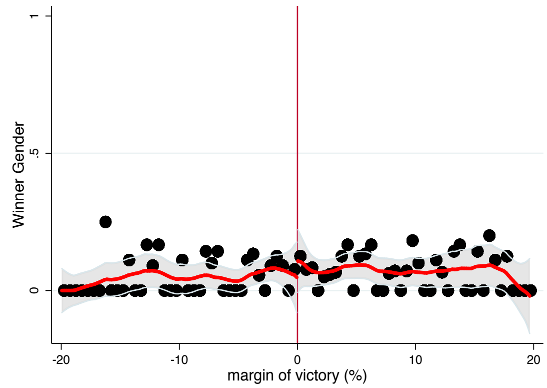
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up.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

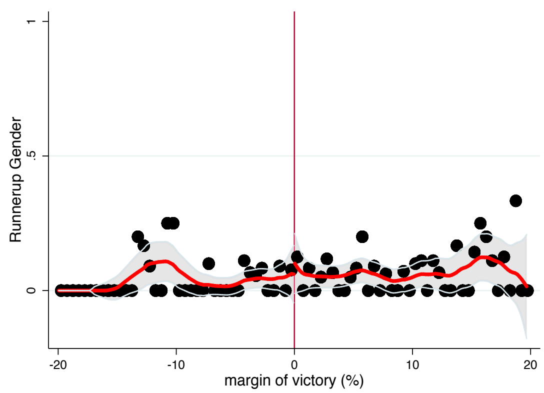
Balance Test for Constituency Characteristics



(j) Incumbent in t-1



(k) Winners Gender in t-1

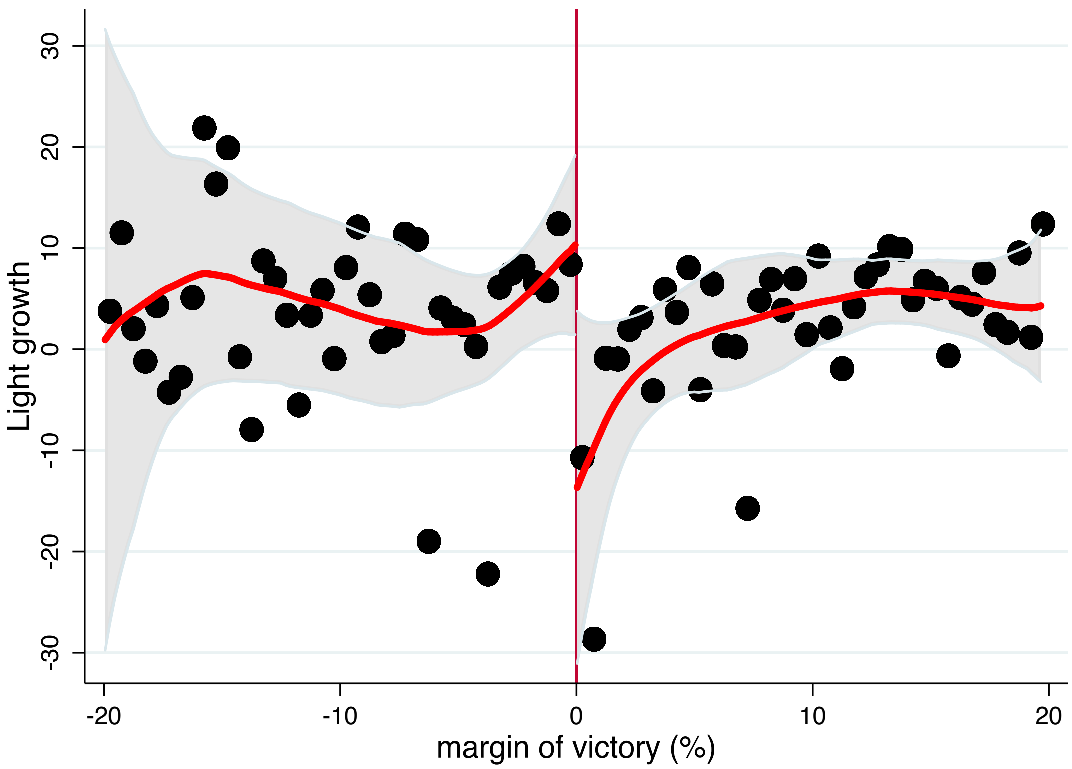


(l) Runners-Up Gender in t-1

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 4

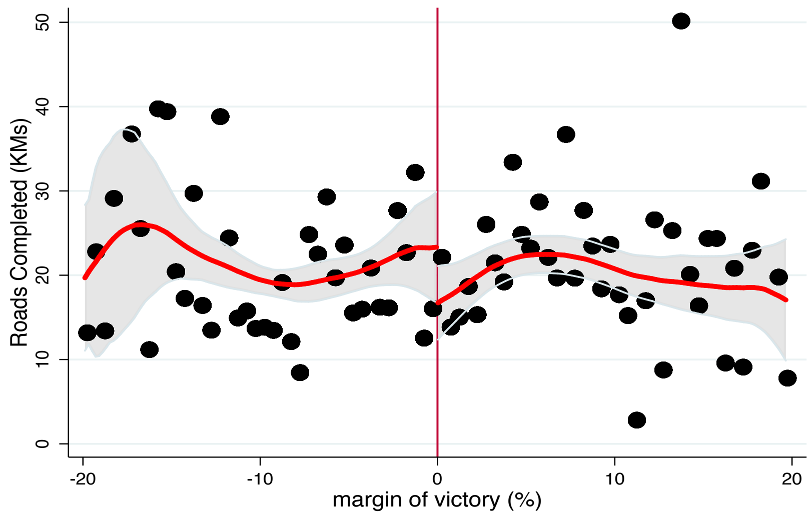
Effect of Electing Criminally Accused Politicians on Growth of Night Lights



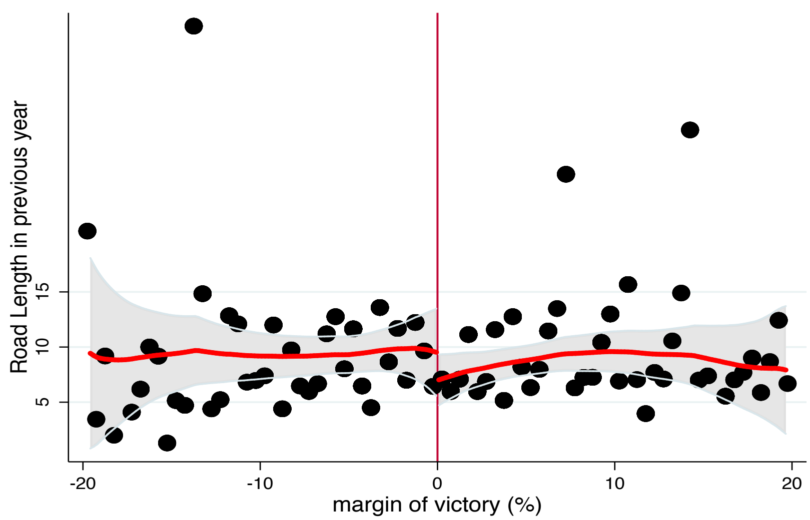
The forcing variable is the margin of victory of a criminally-accused candidate. Negative values are the difference in the vote shares of a criminally-accused runners-up and a non-accused winner. Positive values are the differences in the vote shares of a criminally-accused winner and a non-accused runners-up.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

Figure 5

Effect of Electing Criminally Accused Politicians on Length of Roads Built Annually under PMGSY (in kms)



(a) RD Effect

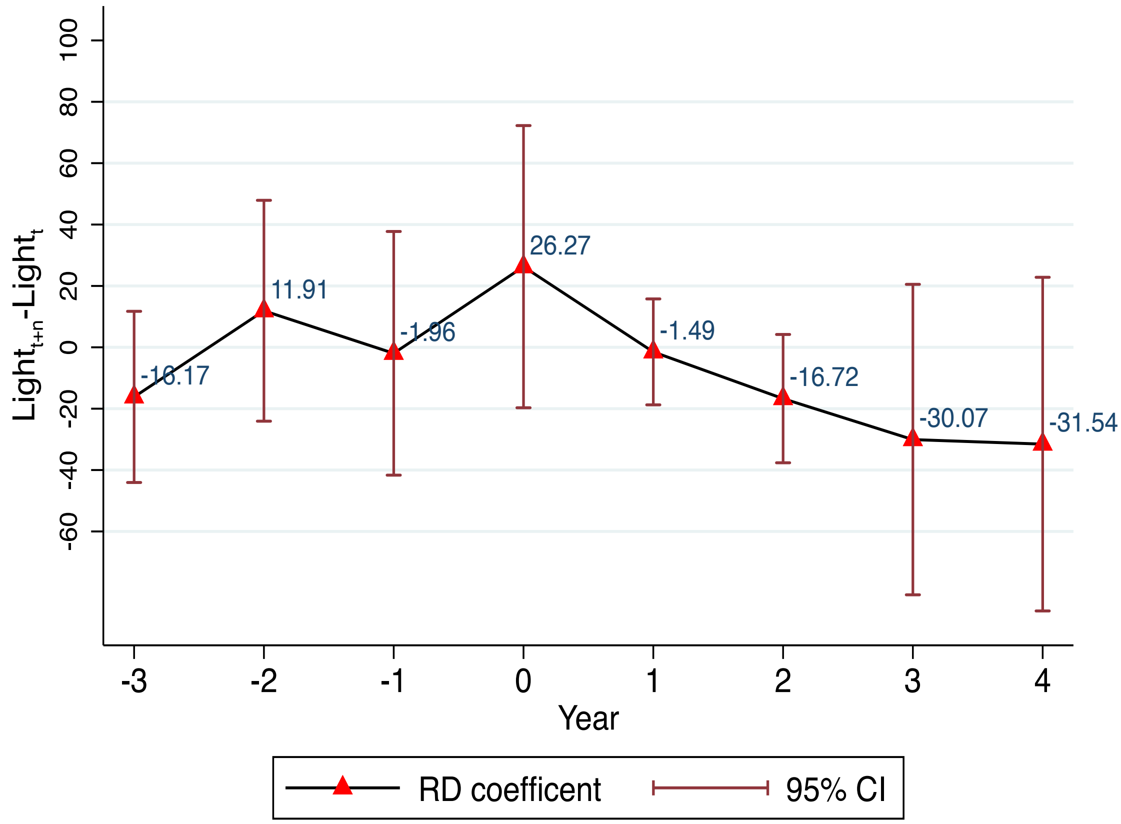


(b) Roads Length t-1

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. The variable on the y-axis is Roads Built Annually under PMGSY (in kms) 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 Kalayanaraman (2012). The confidence intervals are the 95% confidence intervals plotted using standard errors that are clustered at the constituency level.

Figure 6

Effect of Electing Criminally Accused Politicians on Growth of Night Lights by Year in Power



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
Effect of Electing Criminally Accused Politicians by State Characteristics

Dependent Variable	Growth of Night Lights			
	(1)	(2)	(3)	(4)
	PANEL A: Non-BIMAROU States			
Criminally Accused	-4.46	-3.95	-7.08	-2.01
	(3.99)	(3.61)	(6.61)	(2.28)
Bandwidth Size	9.44	10.62	4.72	18.88
No. of observations	1,226	1,335	651	1,910
	PANEL B: Relatively Developed States			
Criminally Accused	-5.77	-4.89	-5.88	-3.17
	(3.86)	(3.16)	(6.23)	(2.27)
Bandwidth Size	9.86	12.73	4.93	19.73
No. of observations	1,270	2,330	700	1,965
	PANEL C: Low Corruption States			
Criminally Accused	-8.30*	-7.78*	-9.9	-5.34*
	(4.50)	(4.32)	(6.48)	(2.96)
Bandwidth Size	8.61	9.27	4.30	17.21
No. of observations	1,263	2,420	695	1,944
Bandwidth Type	IK (h)	CCT	h/2	2h
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 from a separate regression. Panel A includes the non-BIMAROU states: Arunachal Pradesh, Assam, Goa, Gujarat, Haryana, Himachal Pradesh, Kerala, Maharashtra, Manipur, Meghalaya, Nagaland, Punjab, Tamil Nadu, Tripura, and West Bengal; Panel B includes the Relatively Developed states as ranked by Ministry of Finance: Goa, Haryana, Kerala, Maharashtra, Punjab, Tamil Nadu, and Uttarakhand; and Panel C includes the Low Corruption states as ranked by Transparency International India (TII) on index of corruption: Kerala, Himachal Pradesh, Gujarat, Maharashtra, Punjab, West Bengal, Orissa, and Uttar Pradesh. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-2

Effect of Electing Criminally Accused (Serious Charge) Politicians on Roads Built Annually

Dependent Variable	**Length of Roads Built (in kms)**			
	(1)	(2)	(3)	(4)
	PANEL A: All States			
Serious Charge	-8.92	-8.68	-2.41	-4.94
	(5.76)	(5.68)	(6.08)	(4.30)
Bandwidth Size	6.76	7.19	3.38	13.52
No. of observations	351	691	178	525
	PANEL B: BIMAROU States			
Serious Charge	-19.72**	-19.74**	-14.92	-14.66**
	(9.33)	(9.35)	(10.36)	(6.69)
Bandwidth Size	6.54	6.51	3.27	13.07
No. of observations	190	327	106	272
	PANEL C: Least Developed States			
Serious Charge	-19.90**	-20.33**	-16.18	-13.77**
	(9.07)	(9.46)	(10.95)	(6.37)
Bandwidth Size	7.13	6.4	3.56	14.26
No. of observations	205	351	111	294
	PANEL D: High Corruption States			
Serious Charge	-4.8	-6.53	-8.24	-1.29
	(6.97)	(8.76)	(9.41)	(5.44)
Bandwidth Size	7.38	4.14	3.69	14.76
No. of observations	114	205	60	171
Bandwidth Type	IK (h)	CCT	h/2	2h
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 from a separate regression. Panel A includes all the states; Panel B includes the BIMAROU states: Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh, and Uttarakhand; Panel C includes the Least Developed states as ranked by Ministry of Finance: Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh; and Panel D includes the High Corruption states as ranked by Transparency International India (TII) on index of corruption: Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-3

Effect of Electing Criminally Accused (Financial Charge) Politicians on Roads Built Annually

Dependent Variable	**Length of Roads Built (in kms)**			
	(1)	(2)	(3)	(4)
	PANEL A: All States			
Financial Charge	-4.33	-3.4	-2.57	0.34
	(5.65)	(5.80)	(7.25)	(4.42)
Bandwidth Size	9.25	7.54	4.62	18.49
No. of observations	195	319	103	274
	PANEL B: BIMAROU States			
Financial Charge	-10.02	-5.51	-8.91	-4.85
	(7.23)	(8.93)	(9.90)	(5.67)
Bandwidth Size	8.03	4.85	4.02	16.07
No. of observations	104	154	56	140
	PANEL C: Least Developed States			
Financial Charge	-9.76	-7.81	-9.51	-5.53
	(7.38)	(8.46)	(10.22)	(5.43)
Bandwidth Size	7.74	5.77	3.87	15.49
No. of observations	101	170	55	151
	PANEL D: High Corruption States			
Serious Charge	-0.64	2.45	-0.29	2.99
	(6.72)	(7.59)	(7.02)	(5.87)
Bandwidth Size	8.27	4.62	4.14	16.55
No. of observations	85	135	49	118
Bandwidth Type	IK (h)	CCT	h/2	2h
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 from a separate regression. Panel A includes all the states; Panel B includes the BIMAROU states: Bihar, Chhattisgarh, Jharkhand, Orissa, Uttar Pradesh, and Uttarakhand; Panel C includes the Least Developed states as ranked by Ministry of Finance: Arunachal Pradesh, Assam, Bihar, Jharkhand, Odisha and Uttar Pradesh; and Panel D includes the High Corruption states as ranked by Transparency International India (TII) on index of corruption: Tamil Nadu, Haryana, Jharkhand, Assam, and Bihar. The RD estimates in columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-4

Sensitivity Analysis of RD Specification

Dependent Variable	**Growth of Night Lights**			
Type of Accusation	Criminally Accused			
	(1)	(2)	(3)	(4)
Linear	-24.32**	-21.55**	-28.36*	-14.75**
	(10.22)	(8.83)	(15.52)	(6.30)
Quadratic	-30.35*	-30.27**	-28.08	-25.72**
	(15.72)	(14.29)	(21.10)	(10.74)
Cubic	-26.32	-28.74	-20.83	-31.49**
	(19.80)	(18.05)	(25.44)	(14.76)
Quartic	-27.28	-26.54	-12.01	-29.80*
	(23.08)	(21.37)	(27.65)	(17.81)
Bandwidth Size	6.16	7.79	3.08	12.32
No. of observations	1,513	1,742	744	2,429
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 column come from a separate regression. 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 columns (1)–(4) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-5

Effect of Electing Criminally Accused Politicians using Alternate Dependent Variables

Dependent Variable	**Night Lights (in log)**	**Night Lights (in level)**	**Average over Election Term**
	(1)	(2)	(2)
Criminally Accused	-1.21**	-49,898.46*	-24.58**
	(0.49)	(25957.48)	(10.33)
Bandwidth Size	3.76	16.17	6.00
No. of observations	919	2,809	379
Bandwidth Type	Imbens-Kalyanaraman		
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 from a separate regression. 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. Night Lights (in log) is the intensity of night lights in levels; Night Lights (in level) is the light density; and Average Growth over the Election Term is the growth of night lights averaged over the election term of the candidate. The RD estimates in columns (1)–(2) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-6
Addressing Top Coding

Dependent Variable	**Growth of Night Lights**			
	PANEL A			
	(1)	(2)	(3)	(4)
Criminally Accused	-24.73**	-21.82**	-28.44*	-15.11**
	(10.42)	(8.92)	(15.69)	(6.43)
Bandwidth Size	6.02	7.65	3.01	12.03
No. of observations	1,460	3,471	720	2,333
	PANEL B			
Criminally Accused	-24.33**	-21.56**	-28.36*	-14.75**
	(10.23)	(8.83)	(15.52)	(6.30)
Bandwidth Size	6.16	7.79	3.08	12.32
No. of observations	1,513	3,529	744	2,429
Bandwidth Type	IK (h)	CCT	h/2	2h
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 separate regression. 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. Panel A drops any observations where the constituency-year pixel average is 63. Panel B drops any constituency in which the average pixel intensity for any year is 63. 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 A-7

Addressing Extreme Values

Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
	PANEL A: Exclude Growth of Lights > 3 s.d from mean Growth			
Criminally Accused	-7.87**	-7.91**	-6.56	-5.58**
	(3.46)	(3.50)	(4.82)	(2.39)
Bandwidth Size	9.44	9.28	4.72	18.88
No. of observations	1,997	1,972	1,099	2,977
	PANEL B: Exclude Night Lights = 0 (in t or t-1)			
Criminally Accused	-7.80**	-7.62**	-6.75	-5.20**
	(3.48)	(3.41)	(4.85)	(2.37)
Bandwidth Size	9.30	9.66	4.65	18.59
No. of observations	1,969	2,025	1,084	2,961
Bandwidth Type	IK (h)	CCT	h/2	2h
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 separate regression. 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. In Panel A, we exclude growth of lights that is > 3 standard deviation from the mean growth. In Panel B, we exclude night lights with the value = 0 either in period t or t-1. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

TABLE A-8

Controlling for Covariates

Dependent Variable	**Growth of Night Lights**			
	(1)	(2)	(3)	(4)
Criminally Accused	-24.33**	-22.11**	-22.04**	-22.35**
	(10.23)	(9.09)	(9.07)	(9.06)
Bandwidth Size	6.16	6.16	6.16	6.16
No. of observations	1,513	1,513	1,513	1,513
Year Fixed Effects	NO	YES	YES	YES
State Fixed Effects	NO	NO	YES	YES
Control for constituency characteristics	NO	NO	NO	YES
Bandwidth Type	Imbens-Kalyanaraman			
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 separate regression. 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. Column (1) replicates column (1) of Table 3 with no year and state fixed effects; column (2) controls for year fixed effects; column (3) controls for state and year fixed effects; and column (4) controls for year and state fixed effects, lagged growth of night lights (t-1), and constituency characteristics from the previous election: whether the winner was an incumbent, the electoral size, the numbers of voters, total turnout, whether the winner was aligned with the ruling part in the state, the gender of the winner and the runner-up, and whether the constituency was reserved for SC or ST. The RD estimates in columns (1)–(3) are on a local linear regression using a triangular kernel. Asterisks denote significance levels (*=.10, **=.05, ***=.01).

Figure A-7
Share of Criminally Accused Candidates in India