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Crime, Incentives and Political Effort:
A Model and Empirical Application for India

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Crime, Incentives and Political Effort:
A Model and Empirical Application for India[*]

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Abstract

The large share of politicians facing criminal accusations in India has sparked a public debate and an emerging literature that assesses its causes and effects. We develop a model of the incentives faced by members of parliament when deciding whether to engage in effort for their constituency to assess the effect of their having a criminal background on their decision. We use direct and clearly identifiable measures of effort in the 14 Lok Sabha over the 2004-2009 legislative period: attendance rates, parliamentary activity, and utilization rates of a local area development scheme. The findings suggest that criminal MPs exhibit on average about 5% lower attendance rates and lower utilization rates, but no difference in parliamentary activity. The results depend on the development level of the constituency, a proxy for rent-seeking possibilities and monitoring intensity, as well as on the measurement of criminal background. We use selection on observables, matching techniques, and treatment effect regressions to demonstrate why these negative relations should constitute an upper bound estimate for the causal effect of criminality and to show they are unlikely to be driven by selection on unobservabels.

Keywords: India, Elections, Crime, Good and bad politicians, Development, Attendance and activity in parliament, Political economy

JEL classifications: D72, H11, I38

1 Introduction

India 2014: The world's largest democracy still features a parliament where roughly 34% of the recently elected members of the 16th Lok Sabha, the lower house of the Indian parliament, face pending criminal charges against them.[1] A significant share of those face serious criminal charges ranging from murder to the charges of rape.[2] The Indian and international media have reported on this issue, and it is wildly believed that it poses a threat to the Indian democracy in general and the constituencies represented by those individuals specifically. But what are the specific economic and developmental consequences of parliamentarians with pending criminal charges holding public office?

While there is some anecdotal evidence that electoral constituencies represented by Members of Parliament (MPs) with serious criminal charges remain underdeveloped and such members tend to underperform in terms of their effort in parliament, systematic empirical evidence remains scant. Can criminal charges explain variation in parliamentarians' performance in parliament and the development of their electoral constituencies? To explore this question we develop a model of MP incentives in a principal agent approach where the voter takes the role of the principal. The existing literature has modeled the effect of electoral accountability on economic policy choices Besley and Case (1993), of compensation on policy outcomes Besley (2004), and of outside income opportunities on self-selection and behavior Gagliarducci et al. (2011). However, there is to the best of our knowledge no model that has tackled the question of what drives MP effort in parliament, or more specifically for their constituency, once they are elected into office.

We connect to the emerging literature that examines electoral competition in the context of India. For instance, Aidt et al. (2015) investigate why parties field criminal candidates and

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[1] See:
http://timesofindia.indiatimes.com/news/Every-third-newly-elected-MP-has-criminal-background/articleshow/35306963.cms? The members of the 16th Lok Sabha were elected during the 2014 national elections held between 7th April and 12th May 2014. The 16th Lok Sabha commenced on 4th June 2014.

[2] Roughly 21% of the 34% face serious charges such as murder, rioting, theft, kidnapping, rape, etc., see: http://adrindia.org/research-and-reports/election-watch

Dutta and Gupta (2012) analyze competition between candidates that include criminals. In their seminal paper, Besley and Burgess (2002) model incumbents of different unobservable types who can exert effort to help voters in need. Since we focus on the relationship between incumbents and voters, our model is complementary to the first two papers and, in contrast to Besley and Burgess (2002), focus particularly on the behavior and characteristics of criminal incumbents. In our model, MPs are aware that a higher effort level increases the probability of being reelected, but they lose utility from time allocated to political work. Thus, there is a tradeoff between utility and the chance of being reelected. Furthermore, MPs need to take the other determinants of voting decisions into account when choosing their effort level. Using comparative statics with respect to the model parameters we demonstrate, for instance, that the effort of criminal MPs should be relatively higher when they contest in a more developed electoral district.

In order to empirically test our hypotheses we use details about the criminal records of the candidates available thanks to a 2003 Indian Supreme Court judgment that made it mandatory for every candidate contesting state and national elections to provide sworn affidavits. These include details not only about their personal, educational, and financial particulars, but also detailed information on any criminal charges they had faced, the status of their criminal cases and any charges against them.[3] We use criminal charges as a signal whether a MP is a criminal type. To alleviate potential bias in our estimates caused by measurement error due to individual false charges, we run all regressions both with a binary variable *Criminal* coded one for (a) those with a least one charge and (b) for only those with more than one charge. We study the 14th (2004-2009) instead of the 15th Lok Sabha (2009-2014) or a combination of both because a delimitation commission set up in 2002 changed the electoral boundaries of constituencies between the 14th and 15th Lok Sabha elections, making it impossible to match constituencies. Using the 14th Lok Sabha allows us to control for confounding factors such as past electoral performance or party strongholds which are crucial for MP effort.

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[3] The court also asked the Election Commission of India to make it mandatory to publicize the information about electoral candidates provided through these affidavits. Voters can now use this information to make better informed electoral choices.

We want to assess whether elected candidates with criminal records differ from their colleagues with regard to effort. Various measures have been used in the literature to gauge MP effort. Instead of picking just one factor, which might not capture differences between MPs comprehensively, we use three measures that each capture a different facet of MP behavior. First, we use attendance rates (respectively absenteeism) as for example in Besley and Larcinese (2011); Gagliarducci et al. (2010, 2011) and Mocan and Altindag (2013). Second, we make use of MPs effort in parliament by considering information on the number of questions they asked and their participation in debates (cf. Mocan and Altindag 2013, Arnold et al. 2014). While both these measure capture effort, one might question their relevance for the electorate. Using economic outcomes like consumption directly as in Chemin (2012), on the other hand, is rather disentangled from MP behavior, which makes it more problematic to attribute differences to MP effort. Thus, we draw on Keefer and Khemani (2009) and use the cumulative utilization rate of the Member of Parliament Local Area Development Scheme (MPLADS henceforth). The fund is intended for the development of electoral constituencies and offers several advantages in making the effort that MPs make on behalf of their constituencies observable. While details are outlined below, some advantages are that the amounts available are identical across constituencies, implementation of projects requires substantial effort on behalf of the MP, projects are clearly identifiable with the MP's name and the considerable media coverage makes it likely that voters learn about the effort.

The observation level are the 543 constituencies, which each elect one MP in a first-past-the-post-system. We find that across specifications, *Criminal(a)* is related to around 5% higher absenteeism rates. Parliamentary activity, on the other hand, does not differ significantly between criminal and non-criminal MPs in our baseline specification. As suggested by our model, criminal MPs show both significantly lower attendance rates and less parliamentary activity in constituencies that are economically underdeveloped. The reason could lie in better monitoring in the more developed constituencies and/or the greater attractiveness of these constituencies for criminals in terms of rent-extraction possibilities. The coefficients become more negative when we use our *Criminal(b)* indicator instead. MPLADS fund utilization is lower for criminal MPs in general, but only significant for *Criminal(b)*.

The most obvious challenge for econometric identification is posed by omitted variable bias, in particular selection effects. Selection bias could arise if expected effort generally differs in those constituencies that have voted for a criminal MP. The direction of the bias is not ex ante trivial, as we can infer from our model. It would be negative, if, for example, less developed electorates are more likely to elect a criminal and it would be harder to recommend an MPLADS project in such a constituency. A positive bias would occur if less developed constituencies are more likely to elect a criminal and exhibit higher MPLADS utilization rates because it is easier to identify necessary projects. As the common *a priori* assumption is a negative relation between *Criminal* and effort, we would be less concerned about upward bias, because our estimated coefficient would then be an upper bound of the true effect.

As part of our strategy to identify the causal effect of criminal type on the outcome variables, we first use the model as a theoretical foundation to derive an extensive set of relevant constituency- and MP-specific control variables. Second, fixed effects for major states ensure that the results are not driven by factors specific to certain Indian regions such as, for example, economic underdevelopment. Fixed effects for major parties ensure that the coefficient estimates are not driven by unobserved factors specific to a party or related to being part of the government or opposition. Third, we get identical results using alternative matching estimators and show that the control and treatment groups are strongly balanced. Results from treatment effect estimations that model the selection process explicitly yield slightly more negative estimates. For example, when controlling for selection, both *Criminal(a)* and *Criminal(b)* are significantly related to lower development fund utilization rates. This suggests that, if anything, omitted variables and/or selection effects seem to bias our coefficients for criminal background towards zero. For the negative relation between *Criminal(b)* and MPLADS utilization rates, we use selection-on-observables to demonstrate why this is, under relatively mild assumptions, an upper bound estimate. Moreover, we use methods developed in Altonji et al. (2005) to demonstrate that on average selection bias (on unobserved factors) would have to be between two and sixteen times greater than selection on observed factors

to fully explain the negative relation between *Criminal* and attendance rates or MPLADS utilization. As we have plausibly identified the most relevant influencing factors in our model, it seems that criminal MPs are indeed detrimental to their constituency.

The rest of the paper is structured as follows: in the next section we summarize the relevant literature. We then present our theoretical framework yielding some testable hypotheses on the impact of criminal background on parliamentarians' efforts in parliament and the development of their electoral constituencies. Section 4 describes our data, methods and estimation strategy. While section 5 presents the results and discussion, section 6 concludes and give policy implications.

2   Literature

There is a growing literature concerned with the political system of India, and the many challenges that threaten the world's largest democracy, to which our paper connects. Besley and Burgess (2002) explore the relation between electoral accountability and the responsiveness of state governments to falls in production. Their principal agent model highlights the importance of information flowing about politicians' actions. Moreover, in particular the criminalization of politics in India has received much interest. A first strand of literature on this topic is focused on understanding why political parties field candidates with criminal backgrounds in elections in the first place and why voters elect these candidates. This issue has not been subject to intense scrutiny, although a handful of studies do exist. Building on a theoretical model, Aidt et al. (2015) argue and find that political parties in India field candidates with criminal backgrounds when faced with intense electoral competition. One reason brought forward is that such candidates possess certain electoral advantages such as money and "muscle power," which they can use to influence the electoral outcome under conditions of low voter literacy levels and poor electorates. In contrast, Vaishnav (2011) finds no evidence in favor of electoral competitiveness increasing the likelihood of criminal candidates being

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fielded by the political parties in India when examining 28 state elections.[4]

This does not mean that voters are unable to recognize this problem. Dutta and Gupta (2012) reveal that voters actually punish candidates with criminal charges that contest in elections.[5] This suggests that one issue might be the intensity of monitoring by voters: if monitoring costs are too high few might be aware of the candidates' characteristics. In addition, the effects tend to vanish when there are other candidates in the constituency with criminal charges. Under such conditions, the vote share gained by criminal candidates and candidates with enormous declared wealth also tends to increase. These findings are contradicted by Banerjee et al. (2009). Their evidence in a field experiment suggests that voters in rural India tend to vote on caste (ethnic) considerations even after being provided with information on the of criminal background details of the contesting candidates. This suggests that positive preferences for certain characteristics that criminals possess can be enough to trump anti-corruption efforts and help criminal candidates get elected.

The second strand of literature focuses on the consequences of electing candidates with criminal backgrounds. In their state-level analysis covering a period of over 20 years, Kapur and Vaishnav (2011) show the ominous nexus between the candidates contesting elections (especially the ones with criminal background) and the construction sector. Often, the candidates contesting in elections stash their illegal money and assets with builders in real estate in return for quid pro quo benefits. Prior to elections, the illegal money parked in the real estate sector is routed to fund election campaigns for these criminal politicians. Kapur and Vaishnav argue that as a result of this quid pro quo deal the economy grows less in these years, as measured by a reduction in the consumption of cement and other indispensable raw materials.

The studies that come closest to ours are Chemin (2012) and Prakash et al. (2014). Chemin (2012) examines the relationship between parliamentarians in India with criminal backgrounds

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[4] However, he does find the personal wealth of criminal candidates to be correlated with the criminal status of the candidates, suggesting that they could have accumulated wealth over their years of criminal activities. A similar correlation is found by Paul and Vivekananda (2004), who review the information provided by the candidates contesting in the 2004 national elections in India.

[5] Similar such findings in other countries are echoed by Brollo (2010) and Ferraz and Finan (2011).

and consumption levels in their respective constituencies. He finds that poverty levels tend to be higher and consumption lower in constituencies which are repesented by MPs with criminal backgound. The paper by Prakash et al. (2014) examines the economic consequences of Members of State Legislative Assembly (MLAs) with criminal background. Using satellite nightime light data across 20 major states in India, they find that electoral constituencies represented by MLAs with criminal background see a lower level of economic development measuring by nighttime light data. The main drawback of these papers is the lack of explicit transmission mechanisms through which these effects are realized. In general, it is not obvious from the existing literature whether electing candidates with criminal backgrounds can explain differences in parliamentarians' efforts in parliament and the development of their constituencies. There is a vast empirical and theoretical literature on factors determining the performance of legislators. For instance, Svaleryd and Vlachos (2009) and Strömberg(2001, 2004) study the effect of political competition on economic outcomes. Fisman et al. (2014), Ferraz and Finan (2011), and Snyder and Strömberg (2010) examine political competition, media coverage and rent seeking behavior of incumbent politicians. More closely related, Aidt et al. (2015) modeled why parties choose to field a criminal in the first place and Dutta and Gupta (2012) tested empirically how voters respond to criminal charges. Our model thus extends the existing literature by examining whether and how the criminal background of an elected MP is related to differences in their effort in parliament and in developing their electoral constituencies.

3   The Model

We model the interplay between an incumbent parliamentarian and their electorate in a two-period model, similar to Besley and Burgess (2002). Consider an incumbent who was voted into office in a specific constituency at the beginning of period 1. At the end of period 1, the incumbent faces the election for the next legislative period. Voters base their decision in two dimensions: Personal characteristics and political effort exerted by the MP for their constituency.

The personal characteristics of a politician can be understood as capturing anything which can influence the voting decision of a citizen, including gender, age, wealth, party membership et cetera. Suppose there are n such personal characteristics and each characteristic can be expressed in a binary manner (i.e., male or female, old or young et cetera). Then, we may represent the personal characteristics of the incumbent as a n-dimensional vector x, where, for $k \in \{1, \ldots, n\}$, $x_k = 1$ if the incumbent exhibts characteristic 'k' and $x_k = 0$ if she does not. The facet we will focus on later is whether an incumbent is faced with criminal charges. In our analysis, we consider two types of incumbents who exhibit identical personal characteristics except that one has criminal charges against her and the other does not. We refer to the former as criminal (c), and to the latter as non-criminal (n), where we denote the corresponding personal characteristics by x^c and x^n. Let s be the characteristic which represents 'criminal charges', then it holds that $x_s^c = 1$, $x_s^n = 0$ and $x_k^c = x_k^n$ for all $k \neq s$.

In period 1, the politician chooses her effort level $e \in [0, 1]$ which represents time allocated to political work. 'Effort' can be understood broadly as political activity that can be related to her position as the representative and advocate of her constituency. Marginal time costs are assumed to be 1 and linear for simplicity. The reelection probability of the MP, P(e,x) is influenced both by her political effort and her personal characteristics. Let $U > 0$[6] be the incumbent's utility from holding office, then an MP's optimization problem takes the following form:

$$\max_{e \in [0,1]} \; P(e, x) \cdot U - e \tag{1}$$

Voters can learn the effort level of the MP, but learning is costly. We denote the fraction of voters who choose to be informed ι. Being informed requires sufficient access to sources like electronic or print media and the ability and willingness to comprehend the information. Therefore, it seems plausible that a share of voters $(1 - \iota)$, which we can illustratively think of as illiterate, poor or politically less interested, cannot afford or chooses not to learn. However, voters who belong to the latter group are not necessarily completely uninformed. They do not learn the effort level of the MP, but may still know some obvious and easily accessible

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[6] The utility from holding office is assumed to be strictly positive. Otherwise, a rational individual would not run for public office.

personal characteristics x_k of the incumbent and her challengers such as gender, party and caste membership. However, the intensity of monitoring of MP activity is clearly higher with a higher share of informed voters.

The incumbent has the possibility to convince a share of the informed voters to vote for her by exerting political effort in period 1. While we assume a specific functional of this relationship in this section for illustrative purposes, Appendix A shows that the results in Propositions 1 and 2 still hold with more general functions. Let $I(e, x) = \frac{e}{e+m(x)}$ be the fraction of informed citizens who vote for the incumbent where m is a function from the characteristic space into positive reals.[7] Function m can be regarded as a measure for the electoral competitiveness in the MP's constituency. It determines a proportion of the informed population, $\frac{m}{m+1}$, who would not vote for the MP regardless of her effort. The underlying reasons are voters' preferences over personal characteristics.[8] These preferences are constituency-specific: whether the membership in a party P increases or decreases m depends on voters' preferences for P in the respective constituency.[9] There is convincing evidence that a significant part of the Indian population is generally opposed to political criminality (Banerjee et al., 2014). While other reasons contribute to the elections of criminals, Dutta and Gupta (2012) find that, all else equal, voters penalize candidates with criminal charges. In line with the empirical evidence, we hence assume $m(x^c) > m(x^n)$.

The fraction $(1 - \iota)$ of uninformed voters, on the other hand, cannot be convinced by political effort, since they do not learn about effort. Instead, uninformed citizens vote randomly to some degree. Following Besley and Burgess (2002), we assume that the fraction N of

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[7] $I(e, x)$ is similar to the function of Tullock (1980). However, in our model, it represents a fraction of the informed population and not a winning probability.

[8] We have not specified the preferences of voters for simplicity. One may think of, for instance, Euclidean preferences over personal characteristic: Let α_v be voter v's ideal point in the characteristic space, then voter v evaluates a characteristic profile x by $- \parallel \alpha_v - x \parallel$. The existence (resp. non-existence) of a certain characteristic k increases m if k is contained in the ideal points of the majority (resp. minority) of voters.

[9] Because it is not directly relevant for our purpose, we do not model challengers and candidate selection explicitly. It is of course likely that challengers of the incumbent engage in election campaigns. It is plausible, however, to distinguish these election campaigns, which only transport a promise about effort, from the actual political effort which only the incumbent can exert due to his role as an MP. Rather, the strength of candidate competition would enter as a factor in m. The lower m, the higher the fraction of informed voters who can be convinced by a certain effort level of the MP. The empirical application will control for such factors.

uninformed citizens who end up voting for the MP is uniformly distributed on an interval $[a, 2b - a]$ where $1 > b > a \geq 2b - 1$. The parameter b can be interpreted as the expected level of support for the MP, a higher b relates to a higher expected vote share. As argued above, while informed voters choose not to learn about the MP's effort, they still possess information about the candidates like, for example, her name and party membership which are visible to everyone on the ballot sheet. The a represents noise in voting: The lower a the higher the variance, the higher a the lower the variance.

In a first-past-the-post system, the incumbent wins the election in her constituency if

$$\iota I(e, x) + (1 - \iota)N > \frac{1}{2}.$$

By using this condition, one obtains the winning probability of the MP:

$$P(e, x) = \begin{cases} 1, & \text{if } \frac{-1/2 + \iota I(e,x) + (1-\iota)a}{(1-\iota)2(b-a)} > 0 \\[2ex] 1 + \frac{-1/2 + \iota I(e,x) + (1-\iota)a}{(1-\iota)2(b-a)}, & \text{otherwise} \\[2ex] 0, & \text{if } \frac{-1/2 + \iota I(e,x) + (1-\iota)a}{(1-\iota)2(b-a)} < -1 \end{cases}$$

The incumbent wins the election for sure if $(1 - \iota)a > 1/2$ and loses for sure if $\iota \frac{1}{1+m(x)} + (1 - \iota)(2b - a) < 1/2$. In both cases, the optimal effort of the MP is zero. Furthermore, if there exists an effort level $\hat{e} \in (0, 1)$ such that $P(\hat{e}, x) = 1$, it is obvious that the optimal effort level of the incumbent will never exceed $\hat{e}$. We focus on the other cases. The first-order condition of equation (1) is $P'(e, x) \cdot U = 1$ (i.e. the marginal returns to effort equal its marginal costs).[10] This yields

$$z_j = \sqrt{\frac{\iota}{1 - \iota} \cdot \frac{U}{2(b - a)} \cdot m(x^j)} - m(x^j) \tag{2}$$

where $j \in \{c, n\}$.

The optimal effort level of type j is $e_j^* = z_j$ if $z_j \in [0, 1]$, which we call interior solution. If

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[10] Note that there are two effort levels which solve the first-order condition of equation (1). However, the other fails the second-order condition.

$z_j < 0$, then $e_j^* = 0$, and if $z_j > 1$, then $e_j^* = 1$. Assuming an interior solution, we at first consider the impact of the constituency-specific parameters on the optimal effort level regardless of incumbent type. Our results are summarized in proposition 1 below. Afterwards, we compare the optimal effort of a criminal and a non-criminal incumbent.

Proposition 1. The optimal effort level of the incumbent is higher if

(i) voters are better informed (high ι)

(ii) the MP's utility from holding office is higher (high U)

(iii) the expected level of support is lower (low b)

Proof. The proof is trivial by using equation (2) □

Results (i) and (ii) make intuitive sense and do not require much interpretation. Result (iii) together with the result for the case of a certain election victory or defeat can be interpreted as effects of electoral competitiveness. Thus, our model can also help to explain the finding by Keefer and Khemani (2009) that effort levels are generally lower in party stronghold constituencies with little competition. The reason for (iii) is that a lower b decreases the length of the interval for the uniform distribution, i.e. the share of voters who vote randomly. A shorter interval results in less variance in the expected winning probability, hence the marginal effect of effort increases.

As described above, function m differs for a criminal and a non-criminal incumbent. The difference between a non-criminal and criminal incumbent is specified in the following proposition.

Proposition 2. The difference between optimal effort levels $\Delta_{e^*} = e_n^* - e_c^*$ is

(i) positive if the information level (ι) and/or MP's utility (U) is sufficiently low

(ii) decreasing in ι

(iii) decreasing in U

Proof. (i) By using (2), the difference is greater than zero if $\sqrt{M \cdot m(x^n)} - m(x^n) - \sqrt{M \cdot m(x^c)} + m(x^c) > 0$ where $M \equiv \frac{\iota}{1-\iota} \cdot \frac{U}{2(b-a)}$. This condition is equivalent to $\sqrt{m(x^c)} + \sqrt{m(x^n)} > \sqrt{M}$. The left-hand side of the inequality is strictly positive. Furthermore, M is arbitrarily close to zero if ι or U is arbitrarily close to zero. Thus, there exist sufficiently low ι and/or U such that the inequality is satisfied, which proves (i). (ii) Deriving the distance with respect to the information level yields $\frac{\partial \Delta_{e^*}}{\partial \iota} = \frac{1}{2(1-\iota)^2} \cdot \sqrt{\frac{(1-\iota) \cdot 2(b-a)}{\iota \cdot U}} \cdot \left(\frac{\sqrt{m(x^c)} - \sqrt{m(x^n)}}{\sqrt{m(x^n) \cdot m(x^c)}} \right)$ where the first and the second term are strictly positive and the third term strictly negative, since we assumed $m(x^c) > m(x^n)$. Thus, $\frac{\partial \Delta_{e^*}}{\partial \iota} < 0$, which corresponds to statement (ii). Statement (iii) can be shown in analogy. $\square$

When we test these hypotheses empirically, we propose that a high information level as well as utility in form of rent-extraction potential are related to the development level of the constituency. It is not implausible that criminal incumbents experience higher utility from holding office in electoral districts that are economically more developed, because these offer greater potential for rent extraction. In this context, (i)-(iii) from Proposition 2 can be interpreted as follows. For constituencies with a low developement level, criminal incumbents put considerably less effort in political work than non-criminals. If the developement level increases, the effort level of a criminal converges to the effort of a non-criminal. In theory, if the developement level is high enough, the optimal effort of a criminal could even be higher than the effort of a non-criminal. Based on the existing literature and anectdotal evidence, a positive effect seems a priori unlikely. One aspect that points in this direction, which we have not explicitly incorporated in the model, is that criminals can use campaign practices which are not available to non-criminals such as the intimidation of voters or the buying of vote (e.g., Vaishnav, 2012). In the model, this would be best captured by assuming that criminal incumbents can push up the expected level of support b of the uninformed citizens. This has a strictly negative impact on the optimal effort level if the MP is a criminal type due to statement (iii) of Proposition 1, and further increases d.

To summarize, the model shows how MPs' criminal backgrounds can relate to their chosen effort level, by taking account of re-election concerns and incorporating imperfectly informed electorates. We derived that criminal types exert less effort under certain circumstances, but not necessarily in all cases. In particular, the model suggests that a higher share of politically informed voters increases the incentives to engage in effort for all types of incumbents. The model rests on relatively mild and general assumptions, and can be aligned with previous empirical findings and related models. For our empirical application, the model provides useful guidelines for the selection of variables and testable hypotheses.

4   Data and empirical strategy

We use various data sources to construct a constituency-level data set for the 14th Lok Sabha legislative period. We focus on the 14th (2004-2009) instead of the 15th Lok Sabha (2009-2014) or a combination of both because a delimitation commission changed the electoral boundaries of constituencies between the 14th and 15th Lok Sabha elections in 2002, which makes it impossible to match constituencies. Using the 14th Lok Sabha allows us to control for confounding factors such as past electoral performance. This section describes our proxies for the effort level chosen by the incumbent MP, our measure whether an MP is of the criminal type, as well as the proxies for electoral competitiveness, monitoring intensity and candidate characteristics. We use two different measures to gauge the parliamentary performance of MPs, and one indicator to assess constituency development proposed by Keefer and Khemani (2009). All three have the advantage that they can be directly atrributed to actual MP effort.

4.1   Dependent variables:

i) Attendance rates and parliamentary activity

The most obvious measure of MP effort is attendance rates in parliament. This measure has several advantages. First, it is easily measurable and clearly interpretable. Second, it has been widely used in the literature, for example in Gagliarducci et al. (2010, 2011) and Besley and

Larcinese (2011). Mocan and Altindag (2013) and Fisman et al. (2014) use it as their main measure of effort in studies on MPs in the European parliament. To avoid confusion, note that some papers use the absenteeism rate instead, which is of course simply the inverse of our measure. Our variable *attendance rate* is scaled between zero and one. The lowest rate is 6% for former prime minister Atal Bihari Vajpayee from Uttar Pradesh, who has no criminal background, but was already 76 years old at the date of election. The highest rates are 96% for two MP's from Bihar and Manipur, both without any criminal charges against them. The simple correlation between *Criminal(a)* and *attendance rate* is -0.14.

Though *attendance rates* as a measure has many benefits, it does not necessarily correlate with MP's work attitudes and intensity once they are actually present. Therefore, we complement our analysis of MP effort by a second measure of MP *parliamentary activity* within the parliamentary sessions in the 14th Lok Sabha period. The literature has for example suggested using speeches, oral contributions and private initiatives (cf. Arnold et al., 2014) or the number of questions asked (Mocan and Altindag, 2013). We combine two categories, the number of questions asked and the number of debates in which MPs have participated, into one indicator named *parliamentary activity.*[11] It is more likely that voters receive a signal, whether it be via personal investigation or via the media, about the average effort invested into activities by their MP. Hence, an overall indicator is better suited to capture the total effort exerted by an MP inside the parliament and proxy the effort level observed by the voters. We normalize each indicator by dividing it by its standard deviation to achieve comparability, and then take the simple average. This aggregate indicator ranges between 0 for nine MPs who have neither asked any questions nor participated in any debate, to 5.03 for C.K. Chandrappan from Trichur constituency in the state of Tamil Nadu, who asked 415 questions and participated in 113 debates. There is no obvious correlation between *parliamentary activity* and criminal type, the

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[11] We do not use the proposition of private member bills. In the Indian parliamentary system any MP not acting on behalf of the government or political party can introduce a bill in the parliament with the permission of the speaker of the house. The speaker, in consultation with the leader of the house (i.e. the Prime Minister), allots two and half hours on every Friday in each of the parliamentary sessions to discuss the private bills proposed by the MPs. So far, 14 private members bills have been passed in Indian parliament. All of these bills were passed before 1970. Since 1970, not a single private members bill was passed. During the 14th Lok Sabha period a total of 300 private members bills were moved by various MPs, of which a mere 4% were actually discussed (see Kumar 2010).

simple correlation with *Criminal(a)* is a mere 0.003. The data for both *attendance rate*s and parliamentary activity exerted by MPs is taken from the Association for Democratic Reforms (ADR), an independent body that researches Indian elections which was established in 1999.[12]

ii) MPLADS utilization rate

Our third dependent variable is intended to capture MPs' efforts in developing their respective electoral constituencies.[13] We follow Keefer and Khemani (2009) who use utilization of Member of Parliament Local Area Development Scheme (MPLADS) funds meant for development of MPs' constituencies. Introduced in 1993, each MP can receive about 10 million Indian rupees (about 160,000 $US) annually to spend on developmental activities or on local public works recommended by the MP of that constituency. In 1998, it was increased to 20 million Indian rupees. Any unspent money under the MPLADS fund accumulates and is carried forward to the next fiscal year until an MP leaves office. The new MP representing that constituency will inherit the total unspent amount under MPLADS.

The utilization of funds from the MPLADS is a good proxy for the effort exerted by an MP to develop her constituency for several reasons. First, it is noteworthy that the amount (20 million Indian rupees) allotted to each MP every year is independent of an MP's effort and is identical across all the MPs. Utilizing these funds to develop the constituency is purely the prerogative of respective MPs representing their constituencies because the public works which are of utmost importance for the development of that constituency must be identified and initiated by the MP alone. This effectively means that MPs need to exert considerable effort to undertake various developmental works: they must work in tandem with various government bureaucrats at the national and state level to first identify viable projects and then obtain permissions and sanctions for the work and monitor the work once the project is undertaken. Second, the MPLADS permits MPs to take credit for the public works projects undertaken under this scheme. This provides incentives for the MPs to exert effort to develop

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[12] ADR is collecting relevant details about candidates contesting both national and state-level elections in India. See: http://adrindia.org/research-and-reports/election-watch

[13] Note that electoral constituencies in India do not overlap with districts' boundaries in the states.

their constituency. Third, Keefer and Khemani (2009) demonstrate that in the recent years voter awareness of the MPLADS has increased. Thus we can credibly assume that informed voters are aware of their MP's effort. MPLADS utilization is hence a measure of direct relevance for citizens, but in contrast to consumption (Chemin, 2012) and nighttime light intensity (Prakash et al., 2014) can directly be traced back to MP effort.[14]

We use the cumulative utilization rate which is the actual spending incurred by an MP in her constituency as a percentage of the total amount released under the MPLADS each year during the 14th Lok Sabha period. Unfortunately, the data on actual spending under MPLADS are not publicly available for the year 2005. Thus, our cumulative utilization rate includes the data from 2006 to 2008. Note that the actual spending incurred by an MP includes any unspent amount which is inherited from her predecessor. Therefore a higher utilization rate must denote greater effort being exerted by the MP to bring development to their respective constituencies. We obtain the data on the MPLADS funds from the annual reports on the MPLADS published by the Indian Government's Ministry of Statistics and Program Implementation.[15]

The distribution of the dependent variables deviates from a normal distribution to some degree (see Appendix AFigure 2). We will thus replicate our baseline models with the propensity score matching estimator, which requires fewer distributional assumptions. Potential severe outliers might in particular be very high values in *parliamentary activity* and *MPLADS utilization*. We hence also re-estimate our models without these potential outliers in the robustness section.

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[14] For more details on MPLADS, see: http://mplads.nic.in/welcome.html, accessed between March and November 2013).

[15] See: http://mplads.nic.in/Annualreportmenu.htm, accessed between March and November 2013)

4.2   Variable of interest

Our key independent variable is the criminal background of MPs. With the Supreme Court's 2003 order, all candidates contesting state or national elections in India are required to submit a sworn affidavit detailing their criminal background to the Election Commission of India. These are available to voters on the Election Commission's website.[16]They provide information about the number and types of criminal accusations against a candidate, and their number of convictions. We make use of this information to create a binary variable *Criminal(a)* which takes the value of 1 if an MP has any accusation against them and 0 otherwise.

Our aim is to measure the criminal type of an incumbent. Criminal charges provided in the affidavits constitute a good, but imperfect proxy. First, some of the cases registered against the candidates could be politically motivated. However, Vaishnav (2011) argues that information disclosure about criminal charges is obligatory only if the judge deems the charge worthy of a criminal proceeding after a thorough investigation by the local police. Second, candidates may under-report their criminal charges. Still, the potential political costs of under-reporting are high as opposition parties may latch on to the issue, leading to disqualification of the member from the parliament. Still, while we want to identify the MP's true type CR^*, we observe only the affidavits, which transport a noisy signal $CR = CR^* + u$. Measurement error in CR would attenuate its coefficient, i.e., bias it towards zero.

To avoid such problems we also code a variable *Criminal(b)* that only takes the value of 1 if an MP has more than one charge against him. This alleviates concerns about mistaking innocent MPs for criminals insofar as it is less likely that all charges are wrong. Also, for some of the accused MPs, their illegal activities might have been a one-time, unrepeated mistake. *Criminal(b)* is more likely to capture "real" criminal types. The main advantage of this coding approach is its simplicity and its objectivity compared to subjectively rating the

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[16] See: http://eci.nic.in/eci_main1/LinktoAffidavits.aspx and http://eci.nic.in/archive/GE2004/States/index_fs.htm, accessed between March and November 2013. In some cases it is necessary to manually adjust the spelling of names in the different data sources. This was done by comparing the names with the information available at http://ibnlive.in.com/politics/cand2004.php and adjusting the names accordingly.

relative severity of crimes.[17]

MPs with criminal accusations against them are not a phenomenon bounded to few states or certain parties. Table 1 shows that all parliamentary parties are comprised of some criminal members. The share is highest for Rashtriya Janata Dal, a party most prominent in the state of Bihar, with 10 out of 21, or 47.6%, of members being accused of criminal activity. Of the other major parties, the shares range from 15.6% for Indian National Congress to 29% for the Samajwadi Party. The geographic distribution is equally dispersed, as can be seen in Figure 1. Most states have at least one and usually more MPs facing criminal accusations. The highest shares in the major states are to be found in Kerala with 36.8%, Bihar with 38.7% and Maharashtra with 46.2%. Assam constitutes the only larger state without any such MP, and in general the far east of India seems to be mostly free of MPs accused of criminal activity.

4.3 Control variables

Our control variables fall into the three categories electoral competitiveness, monitoring intensity and candidate characteristics. A candidate's personal characteristics can affect their individual re-election probability, which relates to the function $m(x)$ in our model. The affidavits also include details about candidates' total assets and liabilities, educational qualifications, age, gender, and experience in parliament. For age, we use MP age at the time of election in 2004. We dummy code the gender variable giving the value 1 if an MP is male and 0 if female. For education we create an ordinal three category system which assigns a value of 0 if education is not given or indicated as "other" or "literate", 1 if the educational achievement is between the 10th to 12th grade passed, and 2 for all graduate, post graduate or other graduate attainments. For MPs' experience we use a simple count of number of times

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[17] Some crimes could be thought of as more directly related to shirking and negative effects for a criminal's home constituency. Crimes related to corruption like accepting bribes might be particularly problematic in a political context. The problem with this is that it is hard to distinguish crimes unequivocally into those relevant for shirking and/or parliamentary performance and those which are not. Murder for example could be related to pure greed and robbery, but also be committed or commissioned to achieve political goals. A second difference to *Criminal(a)* could be that *Criminal(b)* captures differences in the abilities of 'criminal' MPs, who must not necessarily form a homogenous group, to intimidate and bribe voters. If the latter group can acquire more voters that way, they would also engage in relatively less effort.

the MP has been elected before 2004. It is also a proxy for incumbency advantages or disadvantages, but provides a more nuanced measure of experience which could foster effectiveness in parliamentary work. We calculate net assets as the difference between self-reported data on assets and liabilities and take the logarithm.[18]

In regards to constituency features related to competitiveness and monitoring intensity (the share of informed voters ι), we first control for voter turnout as a proxy for the extent to which voters within a constituency are interested in and informed about politics. A similar argument holds for literacy rates: Aidt et al. (2015) suggest that illiterate voters might be less put off by criminality and easier prey for vote buying and intimidation tactics. Likewise, we also control for the closeness of electoral races in constituencies. We use the margin of victory in terms of difference in the vote share received by an MP against the immediate runner-up in 2004 to control for electoral competitiveness. Keefer and Khemani (2009) argue that it is also a measure of voter attachment. To address this further, we include a variable capturing whether or not a constitutency is a party stronghold. This dummy takes the value 1 if a candidate belongs to a political party that has won elections in that constituency for the last three successive elections in 1996, 1998 and 1999. We also use a dummy variable for those constituencies which are reserved for candidates from Scheduled Castes (SCs) and Scheduled Tribes (STs). [19]

Finally, we use the sum of night lights as a proxy for the economic development of the constituencies. As constituency boundaries do not coincide with the administrative district boundaries there are no official GDP estimates at the constituency level. Henderson et al. (2011), among others, demonstrated how to calculate such a measure and show that it correlates with official GDP growth numbers. Chaturvedi et al. (2011) used nighttime light for a study on income distribution within India. They emphasize that light data have an additional advantage as an objective measure of economic development in countries where official data are either not always available or cannot always be fully trusted. We follow the usual approach and use ave-

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[18]   More specifically, we add the minumum net assets plus the value one to all observations, to avoid the creation of missing values here

[19]   In these constituencies, only members of the respective castes and tribes can be elected into office. All data were collected and coded from publicly available sources, mostly the Election Commission of India. Data on partywise competition since 1977 come from http://eci.nic.in/eci_main1/election_analysis_ge.aspx

rage visible, stable light on cloud free nights, collected by the F16 satellite for the year 2004.[20] We use the tif-image-file from the National Geophysical Data Center and merged it in ArcGIS with constituency boundaries that were shared by Aidt et al. (2015). We then calculated the sum of lights using zonal statistics within the constituencies to proxy for economic development. In more developed constituencies voters have better access to media, are more likely to be interested in politics and hence more likely to be informed about their MP's performance.

The resulting maximum sample size for our estimations varies between 395 and 439. The first reason is changes of the MP during a term period, the possible reasons for which are manifold: From promotion into minister or other superior positions at the state level, planned resignations within the period, expulsions, to the death of the MP. We carefully checked each of these cases with information from the election commission of India and excluded all changes.[21] Data on *attendance rate* and *parliamentary activity* are only available in aggregate form over the legislative period, hence comparing MPs with two years in the Lok Sabha to those with four years is misleading. Appendix A1 shows that a dummy variable coded one in cases where there was a change is not significantly related to either the *Criminal(a)* dummy or the *MPLADS utilization rate*. Hence, dropping out of the sample is not systematic in a problematic way and hence does not pose a concern for our estimations. The second reason is that for six constituencies the affidavits could not be accessed either due to poor quality of the scan or malfunctioning links that could not be repaired. Third, sample size is constrained by our first two dependent variables which are available for 395 out of the 435 constituencies left in the sample.

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[20] For more on this measure, see: http://ngdc.noaa.gov/eog/gcv4_readme.txt. The original description states that "the cleaned up (file) contains the lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded and background noise was identified and replaced with values of zero. Data values range from 1-63. Areas with zero cloud-free observations are represented by the value 255."

[21] http://eci.nic.in/archive/GE2004/States/index_fs.htm, accesssed between September and December 2014.

4.4 Empirical Strategy

We distinguish between the analysis of the dependent variables related to parliamentary work, *attendance rate*s and *parliamentary activity*, and the one relating to *MPLADS utilization*. Both measure slightly different dimensions of MP effort. The former two relate very directly to input and effort, whereas the latter also relates to output and MP effectiveness in promoting the development of their constituencies. We refer to the dependent variables as Ef_i, the effort of an MP in constituency i. What we aim to measure is the Treatment effect on the treated (TOT), where Treatment consists of the MP being of the criminal type ($Criminal(Cr) = \{0, 1\}$). The observed differences in the data might, obviously, capture the TOT, but be affected by selection bias.

$$E[Ef_i|Cr_i = 1] - E[Ef_i|Cr_i = 0] \quad =$$

$$\underbrace{E[Ef_{1;i} - Ef_{0;i}|Cr_i = 1]}_{ATET} + \underbrace{E[Ef_{0;i}|Cr_i = 1] - E[Ef_{0;i}|Cr = 0]}_{Selection Bias}$$

The coefficients related to *attendance rates* and *parliamentary activity* as proxies for Ef_i would be upward biased, for example, when constituencies that are more likely to elect a criminal are also those that engage in less monitoring of MP activities. Upward biases ($E[Ef_{0;i,t}|Cr_i = 1] - E[Ef_{0;i}|Cr = 0] > 0$) would also occur when certain constituencies are both more likely to elect a criminal MP and have higher MPLADS utilization rates. For example, poor constituencies with a lower information level could be more likely to elect a criminal MP, and at the same time it is easier to think of and recommend a project in a less developed environment. In this case, our estimates would be biased against finding a negative effect of *Criminal*. Downward bias ($E[Ef_{0;i,t}|Cr_i = 1] - E[Ef_{0;i}|Cr = 0] < 0$) is possible if it would, for instance, be harder to find and develop projects in constituencies that are more likely to have a criminal MP.

Our first attempt to avoid selection bias is, as usual, by carefully selecting an extensive set of control variables and relying on the conditional independence assumption. In doing so, our theoretical model provides guidelines as to the areas from which to select relevant control variables. We estimate

$$Ef_i = b_0 + b_1 Cr_i + b_2 X_i + b_3 S_s + b_4 P_P + \varepsilon_i$$

where Ef_i indicates effort in one of the three dimensions in constituency i, $Criminal(Cr_i)$ is our dummy for whether the MP has a criminal background, X_i is the matrix of control variables in the three categories electoral competitiveness, monitoring intensity and candidate characteristics as specified above, and S_s and P_p are dummies for states and parties respectively. We follow Keefer and Khemani (2009) and use dummies for all major states. As outlined above, criminal MPs are found all across India, but some of the larger states obviously exhibit a higher percentage than others. With the fixed effects we make sure our results are not caused by unobservable, time-invariant factors that are specific to, for example, Maharashtra which has the highest share of MPs with criminal charges.[22] With regard to parties, we choose to employ party dummies as additional controls for all parties that are comprised of twenty or more MPs. The distribution of MPs by party and the respective share of *Criminal* is provided in Table 2.

While we demonstrate in our model that it is not obvious that MPs with criminal charges actually execute less effort than others, the press coverage, as well as public opinion and existing research, suggest a negative coefficient for *Criminal*. If this a priori assumption is true, we would be less concerned about upward bias in the coefficient of *Criminal* ($E[Ef_{0;i}|Cr_i = 1] - E[Ef_{0;i}|Cr = 0] > 0$). Our estimates would then pose an upper bound of the (more negative) causal effect. We will show various pieces of econometric evidence in the analysis that suggest upward bias is more likely than downward bias.

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[22] Smaller states like the union territories Andoman and Nicobar have only one or very few MPs, hence there is also no within-variation in the variable *Criminal*. A full list of the states and the respective share of criminal MPs is provided in Appendix table A1.

We use cluster-robust standard errors that allow arbitrary within-cluster correlation. With regard to parliamentary work, correlations between individuals' efforts are arguably most likely within parties. Parties are the natural unit of comparison within a parliament; MPs are, for example seated along with their own party members. Thus, we choose the party level as the clustering unit for the first two variables. For the MPLADS fund, on the other hand, outcomes within states are more likely to be correlated and we cluster on the state level. The implementation probability and effectiveness depends on the individual state, which processes and executes the projects. Some states might, for example, be quicker in implementing the proposals than others; and differences in ex ante success probability can affect the likelihood of applying for a project. We now turn to our results.[23]

5   Results

5.1   Baseline

Table ATab 2 in the appendix depicts the baseline results for the regressions for *attendance rates, parliamentary activity* and *MPLADS utilization* as dependent variables. All regressions contain state dummies and dummies for the major national parties State dummy coefficients are not displayed to improve clarity and readability. *Attendance rates* ranges from 0 to 1, *parliamentary activity* from 0 to 4.38 and *MPLADS utilizatio*n from 60.5 to 260.

Let's consider *attendance rates* first. The omitted reference category for the major party dummies are other or non-national party MPs. Positive relations with *attendance rates* compared to this reference category can be seen for the "Indian National Congress" and the "Samajwadi

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[23] The number of clusters, 42 parties for parliamentary work and 33 states for the MPLADS fund, should be sufficiently high not to suffer from 'few cluster' inference problems. Our main results are virtually unchanged when clustering on either state or party. Recently, MacKinnon and Webb (2015) also suggested that inference might be affected by wildly different cluster sizes. We programmed a cluster wild bootstrap procedure based on the suggestions in their appendix and Cameron et al. (2011). To generate the bootstrap dependent variables we used the "Rademacher" 2-point distribution as well as the "Webb" 6-point distribution. The results with 10,000 repetitions mostly confirm the findings with more standard procedures. *Attendance rates* remains significant with *Criminal (a)* (Rademacher p-value=0.066/ Webb p-value=0.063) and *Criminal(b)* (Rademacher p-value=0.009/ Webb p-value=0.010), and *parliamentary activity* remains insignificant. The only difference is for MPLADS utilization rates, where *Criminal(b)* becomes marginally insignificant ((Rademacher p-value=0.139/ Webb p-value=0.125)

Party", significant at the 1% and 5%-level, respectively. For *parliamentary activity* the positive effect of "Indian National Congress" disappears and we observe a negative relationship with being a member of the "Communist Party of India". It is positively related with the "Rashtriya Janata Dal" and the "Samajwadi Party". The only significant party for *MPLADS utilization* is a negative relation to "Indian National Congress".

For *attendance rates*, MPs from constituencies that are reserved for religious or caste minorities show significantly higher *attendance rates* of about 6% compared to their colleagues, significant at the 1%-level. Winning margin, proxying for lack of competitiveness, is as predicted negatively related to all measures of effort, and significantly so for *attendance rates*.[24] A ten percentage point increase in the winning margin translates into roughly 2% lower *attendance rates*. Party stronghold is not significantly related to effort in any of the specifications, conditional on controlling for winning margins. Voter turnout in 2004 is negatively related to effort, significant for *attendance rates*. The negative relationship is somehow surprising, but we should not forget that this is conditional on other proxies that might already capture the positive component of more monitoring already. Economic development, measured by luminosity, is significantly positively related to *parliamentary activity*, and literacy rate is significantly and positively related to *attendance rates*.[25] A 10% higher voter literacy rate translates into 2% higher *MP attendance rates*.

Conditional on all other factors, age and education are significantly and positively related to *attendance rates*. A five year age difference translates into about 1% higher *attendance rates* for the older MPs. Higher education also relates to less absenteeism: possessing a tertiary compared to only a secondary degree relates to about 2.5% higher *attendance rates*. Experience in parliament and Gender are not related to *attendance rates*; however, there is a

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[24] The number of voters as a proxy for constituency size, which Aidt et al. (2015) related to the likelihood that a criminal MP can intimidate a significant share of voters, is not systematically related to our dependent variables in any specification and has no effect on our variable of interest. Thus, we refrain from including it. Including it affects none of our results.

[25] Economic Development relates to better access to media and other information sources, and hence a higher probability that voters get to know about their MP's effort. Economically more well off voters are also more likely to be politically interested and concerned with MP performance. One could speculate that retrieving information about parliamentary activity involves more effort and cognitive ability on behalf of the voters than simple *attendance rates*.

negative relationship between Net Assets and attendance, which is significant at the 5%-level. In addition, being male seems to be positively related to parliamentary activity. We regard this intensive discussion of the conditional factors as justified due to the role they play in our model; however the rest of our tables will omit these coefficients to enhance clarity for the reader.

5.2   Parliamentary Work

In Table 3, we now turn to the relationship between our main variable of interest and *attendance rates*. *Criminal(a)* has a coefficient of -0.047 which is significant at the 10%-level in column 1, when controlling for state and party dummies only. The coefficient becomes slightly more negative in columns 2 and 3 when we add controls for electoral competitiveness and monitoring intensity, and significant at the 5%-level. This indicates that omitting the two categories leads to a slightly upwardly biased coefficient. The coefficient changes marginally to -0.043 when including candidate characteristics, and remains significant.

The results look rather different when it comes to *parliamentary activity*. As the simple correlation has suggested, there is no systematic relationship between *Criminal (a)* and *parliamentary activity* in columns 5 and 8. The coefficient is negative from column 7-9, however it fails to be significant in any. Thus there seems to be on average no significant difference between MPs of different types with regard to *parliamentary activity*. This demonstrates that contrary to public opinion, criminal MPs do not necessarily exhibit less effort in all dimensions. This is in line with our model which demonstrated that whether criminal MPs choose less effort depends on the circumstances and other model parameters.

Using our alternative and more stringent measure *Criminal(b)*, which should alleviate measurement error problems in identifying criminal types, confirm and strengthen the existing results. For *attendance rates*, the coefficient for *Criminal (b)* increases in absolute size from about 4% to about 12% lower *attendance rates* for those with a criminal background (column 9-12). This effect is significant at the 1% level. Similarly, the coefficient for *parliamentary ac-*

tivity becomes more negative, but is still relatively far from being significant (column 13-16). These two results would be in line both with measurement error in identifying the criminal types and a story where the severity of criminal background relates to bigger differences between criminal and non-criminals. While we cannot fully resolve this issue, tests using the number of crimes and its square instead does not support the existence of a non-linear relationship. In conclusion, we find a generally negative and significant relationship between *Criminal* and *attendance rates*, and a negative but insignificant relationship to *parliamentary activity.*

We further want to test whether the effect of *Criminal* is moderated by monitoring (economic development and literacy rate), as suggested by our theoretical model, and competitiveness (party stronghold and winning margin). We hypothesized that a high degree of information and hence monitoring of MP activity has a moderating effect, as a criminal MP who would choose less effort might not do so when the negative impact she has to fear on her chances for re-election is sufficiently high. Competitiveness on the other hand should not have a significant moderating effect, as it affects criminals and non-criminals alike. Economic development proxies for both access to media and information about candidate performance, and for the average voter's interest in MP effort. Negative consequences of shirking for the MP are more likely in constituencies with a high degree of monitoring, i.e., where voters are better informed and more interested in their MP's performance. To test these hypotheses, we interact *Criminal(a)* with party stronghold, winning margin, economic development and the literacy rate.

Table 4 shows the coefficients for *Criminal(a)* and the respective interaction. All other variables are included but not displayed in the table. The results for both dependent variables show no significant interaction effects with party stronghold and margin (2004), as expected, but also none for literacy rate. However, the interaction effects between economic development and *Criminal(a)* are positive and significant at the 1%-level for both *attendance rates* and *parliamentary activity.* Drawing on our model, one explanation is better monitoring in

the more developed constituencies. An alternative explanation within our model framework, which would be supported by anecdotal evidence, is that part of an MP's utility can come from rent extraction (cf. Fisman et al., 2014 and Kapur and Vaishnav, 2011). If more developed constituencies offer better rent-seeking opportunities for criminal MPs, this increases the utility from re-election, and can also narrow the effort gap between criminal and non-criminal types.

Figures 2 and 3 illustrate the moderating effects. The y-axis displays the effect of *Criminal(a)* on effort with its 95% confidence-interval conditional on economic development, which is plotted on the x-axis. In addition, we plot the 95% confidence interval. The marginal effect of *Criminal(a)* is negative and significant for low *(parliamentary activity),* respectively low and median levels *(attendance rates)* of economic development. These are constituencies where intense monitoring of MP's effort and access to such information is limited, with on average less resources and wealth. For highly developed constituencies there is no significant difference between MPs with and without criminal charges, in line with our model.

The insignificance of the interaction with literacy rates, which also proxies for monitoring, suggests that rent-seeking rather than monitoring is the more likely explanation. Further tests revealed that the interaction with economic development remains significant, even when controlling for literacy rates, while the interaction with literacy rates remains insignificant even when omitting economic development. Thus, our at first sight counter-intuitive result could be understood in a way that more rent-seeking opportunities, usually considered a negative feature, seem to alleviate the negative relation between an MP's criminal background and their parliamentary work.

5.3 Member of Parliament Local Area Development Scheme (MPLADS) utilization rate

Now we turn to *MPLADS utilization,* which as Keefer and Khemani (2009) argue offers several advantages as a measure of MP effort. The baseline model specification is identical to the one for the first two indicators, except that standard errors are now clustered at the state level to allow for arbitrary correlation within states. As implementation of the project depends on the state bureaucracies, correlation within states is most likely. Our results are, however, unaffected by alternatively clustering on parties. Columns 1-4 in Table 5.1 show the results for *Criminal(a)* and columns 5-8 for *Criminal(b).* Columns 1 and 4 use only party dummies, columns 2 and 5 add the electoral competitiveness controls, columns 3 and 6 the monitoring intensity controls, and columns 4 and 8 the candidate characteristics.

For our variables of interest, the coefficient on *Criminal(a)* is negative, but remains insignificant in columns 1-4. The coefficients barely change when adding the controls, becoming slightly more negative in column 4 compared to column1. Thus,we cannot reject the hypothesis that candidates with criminal charges against them generally perform equally well in terms of making use of the development fund scheme. As mentioned above, one concern about these results, however, could be whether the existence of any charge correctly identifies criminal types of MPs. We again use our *Criminal(b)* measure to alleviate these concerns. Columns 5-8 show the results when using the alternative measure. *Criminal(b)* is related to lower utilization rates in all specifications, significant at the 5%-level. This holds when adding the controls: the coefficient becomes slightly more negative from -7.436 in column 1 to -7.723 in column 4. The coefficient translates to about 7.5 percentage points lower cumulative utilization rates over the legislative period.[26]

The obvious question is whether this relationship has a causal interpretation, or if the coefficient is biased upwards or downwards. In our model with two types of fixed effects, identification relies mostly on within-state, within-party variation. Hence, the results should not

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[26] *Criminal(b)* seems to succeed in identifying criminal types in general, alternative specifications using the number of criminal charges and a quadratic term show no indications of a non-linear effect.

be driven by the geographic or political distribution of criminal MPs. Nonetheless, the coefficient might be biased if there are unobserved variables that vary within states or parties and are related to characteristics that affect MPLADS spending. One possibility is, for example, that constituency-specific characteristics like differences in the level of economic development make it easier (or harder) to utilize available MPLADS funds. We can compare the results with and without control variables to get a first indication of the direction of a potential bias. The idea is similar to Altonji et al. (2005): we use selection on observables to assess the effects of selection on unobservables. We observe that, when adding controls X_i, i.e., controlling for selection on constituency and candidate observables, the coefficient becomes slightly more negative in column 4 compared to column 1 of Table 5.1. This shows first that the coefficient is barely affected by observable selection effects. In addition, if omitted variables bias in terms of selection on unobservables works in the same direction as selection on observables, the negative coefficient will be an upper bound estimates of the true causal effect.

Let us briefly elaborate on this argument. Assume the true regression is $Ef_i = \beta_0 + \beta_1 Cr_i + \beta_2 X_i^* + \varepsilon_i$. If we estimate unconditionally $Ef_{i,s} = b_0^U + b_1^U Cr_{i,s} + \varepsilon_{i,s}^U$ instead, where the superscript U stands for the unrestricted model, our coefficient is biased: $b_1^U = \beta_1 + \beta_2 \frac{Cov(C,X^*)}{Var(C)}$, where the second term indicates Omitted Variable Bias (OVB). Now assume our proxies for the three categories that are contained in the matrix of control variables X_i do not capture the true X_i^*, but $X_i = X_i^* + u_i$. For example, it is reasonable to assume that our proxy for economic development is a noisy measure of the true development level. The restricted model with the controls then is $Ef_i = b_0^R + b_1^R Cr_i + b_2^R X_i + \varepsilon_i^R$. We know that measurement error does not affect the covariance of X_i with Cr_i, but it will underestimate the relation between X_i and Ef_i, hence $b_2^R < \beta_2$. Accordingly, positive OVB ($b_2 \frac{Cov(C,X)}{Var(C)} < \beta_2 \frac{Cov(C,X^*)}{Var(C)}$) occurs for $\beta_2 > 0 \wedge Cov(C,X) > 0$ and negative OVB ($b_2 \frac{Cov(C,X)}{Var(C)} > \beta_2 \frac{Cov(C,X^*)}{Var(C)}$) for $\beta_2 < 0 \vee Cov(C,X) > 0$).

How does this help our interpretation? Generally, we are less concerned with OVB when it works against the direction of our estimated coefficient, i.e. a positive bias with a negative

coefficient and vice versa. In the case of MPLADS, our $\beta_1^U < 0$ (column 1), and $\beta_1^R < \beta_1^U$ (column 4), which suggests a positive bias. We can now deduce that even if our empirical proxies only capture the underlying parameters with random measurement error, it holds that $b_1^U < b_1^R < \beta_1 \ \forall \ \beta < 0, b < 0$, i.e. the negative coefficient b_1^R that we report is an upper bound estimate. The assumptions in this consideration are that we have indeed identified the relevant categories in our theory, and that measurement error is random.[27] If our model failed to identify the relevant control categories, selection on other unobservable factors could still be relevant. For this reason, we will conduct further robustness tests for all dependent variables in the next section.

Another way to assess omitted variables is to add the cumulative utilization rate in the previous period to the equation. As constituency delimitation did not change between 1999 and 2004, this should capture any time-invariant omitted factors, i.e., work similar to a constituency-fixed-effect. The coefficient of *Criminal(b)* in column 1 in the second part of Table 6 remains virtually unchanged, giving no indication of such a bias. As another possibility, we consider whether leftover funds from predecessors bias the coefficient. The setup of the MPLADS funds determines that unused resources can be carried over to the next year(s). Higher leftovers increase the overall amount of available money and could bias the measured degree of utilization upwards in cases where there are systematic differences across constituencies. While theoretically plausible, this does either not play a large role in reality, or does not vary systematically between candidates with and without criminal charges, as the coefficient again remains nearly unchanged in size and significant at the 5%-level (column 2).

In addition, we follow the robustness checks in Keefer and Khemani (2009) and test whether political and social fragmentation, as well as electoral volatility in the constituency influence

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[27] The argument holds for a negative estimated coefficient even with systematic measurement error as long as β_2 and $Cov(C, X)$ do not change signs. Even if X systematically under- or overestimates X^*, it follows from $b_1^R < b_1^U$ that $b_1^U < \beta_1 \ \forall \ \beta, b < 0$. Accordingly the negative b_1^U is the upper bound estimate. b_1^U is also negative and significant in the case of *Criminal(b)*, which suggests that the true effect is negative as well. For simplicity other covariates were disregarded here; however, their inclusion would (under standard assumptions) not affect the results . The argument cannot be applied for the estimated coefficients on *attendance rates* and *parliamentary activity*, where selection on observables does not clearly indicate a direction of OVB

the coefficient (columns 3-5). The original data source for the first two measures is Banerjee and Somanathan (2007). They argue that political fragmentation may reflect greater electoral competitiveness, which as we derived in our model can affect an MPs' effort. The measure is defined as $1 - \sum_{i=1}^{N} \mu_{i,C}^2$, where μ_i is the vote share of the ith political party contesting election from the constituency, which is then averaged over the 1991, 1996, 1998 and 1999 elections. Social fragmentation might be relevant if it reduces the provision and changes the composition of local public goods within constituencies. We use a measure of caste and religious fragmentation, based on the census of 1991. Keefer and Khemani (2009) also argue that electoral volatility can be related to MP behavior, as in constituencies where voters are prone to greater shocks and a more unsecure environment, the return to effort by MPs should be lower. As in their study, we use a measure from Nooruddin and Chhibber (2008) that defines volatility as $\frac{1}{2} \sum_{i=1}^{N} | \mu_{i,t} - \mu_{i,t-1} |$, i.e., the sum of the changes in vote shares of N political parties. This is again averaged over the four previous elections. All three measures might lead to omitted variable bias if they are related both to MPLADS spending and to the likelihood of having a criminal MP. However, this does not seem to be the case. The coefficient of *Criminal(b)* remains negative, nearly unchanged in size, and significant in all specifications (column 2-6). Even when we control jointly for all three variables from Keefer and Khemani (2009), the cumulative utilization rate in the previous period and leftover funds from predecessors, the coefficient remains stable and significant at the five percent level. *Criminal(b)* is related to about 7.6% lower utilization rates.

It can be seen in the Violinplots for all dependent variables in Appendix AFigure 2, that the distribution of the utilization rate exhibits some potential outliers in its right tail. To make sure these do not distort our results, column 7 of Table 5.2 drops the ten constituencies with the highest utilization rates that constitute this tail. The coefficient becomes somewhat smaller in absolute size, but remains significant. Finally, we compare *Criminal(b)* only to the MPs without any charge at all, i.e., those who are most likely not of the criminal type. As we would expect, this leads to a larger negative coefficient which also remains significant at the 5%-level. Thus, we conclude that there is a negative relationship between criminal background and development fund utilization, which is significant for those MPs with at least

two criminal charges, and unlikely to be explained by selection or omitted variable bias.

5.4   Identification of causal effects

This section discusses whether our estimated effects capture the causal effect of criminal type, by incorporating additional methods for all dependent variables. First, we employ propensity score matching techniques as an alternative estimator to examine whether this affects our results. Second, we analyze whether the results are driven by extreme values or outliers. The results in Table 6 mostly confirm our above result, however they suggest a stronger negative relationship with criminal background.

So far, we have relied on a regression framework to examine our hypotheses, while matching criminal to non-criminal MPs seems to be an intuitive alternative to assess the treatment effect on the treated. Angrist and Pischke (2008) argue that OLS regressions are a natural starting point for empirical studies. Propensity score matching has advantages but requires many somewhat arbitrary choices which can greatly affect results; and in cases where both are consistent OLS is more efficient. Using matching as a robustness check has two advantages. First, it allows us to compare our regression estimates to those from matching the MPs with criminal background (treatment group) to those without (control group). This is interesting as the weights differ between the two estimators: OLS assigns the highest weights to the observations with the largest conditional variance of the treatment status, whereas matching assigns the highest weight to those observations that are most likely to be treated. Second, we can use matching diagnostics to examine how well the treatment and control group are matched to assess the reliability of our estimates.

We use nearest-neighbor (NN) matching with the Mahalanobis distance-metric and robust standard errors (Abadie and Imbens, 2009). As NN-matching estimators were shown to be inconsistent when matching more than two continuous covariates, we use the consistent bias-corrected estimator as outlined in Abadie and Imbens (2006, 2011), which uses a linear

function of all covariates as a correction term. We show results for the average treatment effect on the treated both when matching to the two or three nearest neighbors. In our case the choice of three offers the lowest median bias in covariate balancing. Covariate balancing seems to be achieved overall: There are no significant differences in the means of any covariate except education which is higher for non-criminal candidates (details in Appendix AFigure 3). If higher education would be related to easier usage of MPLADS funds, for example, this could affect our estimates. However, matching exactly on education level (results available on request) does not alter any of our results.

In a nutshell, the results using matching estimators confirm the regression results both in direction and significance. Column 1 in Table 6 shows that the negative relationship for both *Criminal(a)* and *Criminal(b)* with *attendance rates* becomes stronger but similar in size to the regression results and is significant at least at the five percent level in all specifications. Column 2 confirms that *parliamentary activity* is not generally affected by criminal background. Column 3 for *MPLADS utilization* points in the same direction: the estimated coefficients become more negative. With matching, the negative coefficient of *Criminal(a)* becomes significant at conventional levels when matching on the two nearest neighbors. *Criminal(b)* remains significant, now at the 1%-level, with a more negative coefficient that is again more negative than *Criminal(a)*.

We have already used selection-on-observables to argue why selection bias is less of a concern for the relationship with MPLADS utilization under relatively mild assumptions. Due to the different direction of selection-on-observables, the same argument does not hold for the first two dependent variables. If we do not fully capture the difference in competitiveness and monitoring between those constituencies with and without a criminal MP, unobserved factors could affect the estimates for *attendance rates* and *parliamentary activity*. Theoretically, we would want an instrument that affects the treatment, i.e. the selection of a criminal MP, but is not related to MP effort. One possible instrument is to use the existence of other criminal candidates in the same constituency in the 2004 election. Dutta and Gupta (2012) find that

the fielding of such candidates by other political parties attenuates the stigma associated with criminal background. This would not directly affect incumbent effort if the criminal candidates were not relevant for the final outcome of the election. A crude test of exogeneity shows that it is not significant in the main equation conditional on the other variables in X_i. The instrument would be significant in the first stage, but the F-statistics are comparatively small and the Kleibergen-Papp rk LM and F-statistics do not confirm the validity of the model. This is why we refrain from using an IV strategy.[28]

Instead, we further approach potential selection issues by using so called endogenous binary-variable models (treatment effect models). The approach of these Heckit-models is similar to Heckman selection-models: The selection problem is solved by explicitly modeling selection instead of only proposing a supposedly exogenous instrument. Treatment effect regression differs from sample selection models as the dummy treatment variable is directly entered in the regression equation and the outcome variable is observed for both the treated and the untreated subjects. The advantage of this potential outcome model is that it provides information about the effects of non-linear selection bias.

Specifically, we model two equations. Our simplified regression equation is $Ef_i = \beta X_i + \gamma Cr_i + \varepsilon_i$ where X_i contains the controls and fixed effects and Cr_i is the dummy treatment indicator. Our probit selection equation estimates the latent variable $Cr_i^* = z_i\gamma + u_i$, with

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[28] Chemin (2012) suggests a regression discontinuity design as an alternative, where he focused on cases where a criminal contested against a non-criminal. We do not use RDD in our main specification for several reasons. First, while the treated and control groups seem to be balanced within a +/-5% vote score difference, the assumption of continuous density in the neighborhood of the discontinuity is rejected by the McCrary-test(McCrary, 2008). Specifically, criminal candidates seem to win close elections much more often than chance would predict, as indicated by the higher density to the right of the discontinuity. This apparent score manipulation makes us skeptical about the use of RDD here. Moreover, the number of close races between winner and runner-up is very limited. If we use an already wide bandwidth of 10 (20) percent vote difference, we are left with 31 (62) observations. The interested reader can find these statistics and graphs in the Appendix AFigure 5 and 6. Graphically, one can spot an obvious discontinuity with regard to *attendance rates* and potentially for *parliamentary activity*: Using a simple specification with a regular and quadratic score variable, the difference between Criminals and Non-Criminals becomes more negative compared to our main model and remains significant at the 5%-level for *attendance rate*. *Parliamentary activity* becomes negative and significant as well.

$$CR_i = \begin{pmatrix} 1 & \text{if } CR_i^* = z_i\nu + u_i > 0, \\ 0 & \text{if } CR_i^* = z_i\nu + u_i <= 0 \end{pmatrix}$$

and $Prob(Cr_i = 1 \mid z_i) = \emptyset(z_i\gamma)$, respectively, $Prob(Cr_i = 0 \mid z_i) = 1 - \emptyset(z_i\gamma)$.

ε_i and u_i are assumed to be bivariate normal with zero mean and covariance matrix $\begin{pmatrix} \sigma_\varepsilon & \rho \\ \rho & 1 \end{pmatrix}$.

$\rho \neq 0$ reflects the assumed endogeneity of the treatment, and $\sigma_u^2 = 1$ for identification.

This is a switching regression depending on whether $Cr^* > 0$ or $Cr^* < 0$, with separate

forms for the outcome under treatment $(E_{i,g} = x_{i,g}\beta + (z_{i,g}\nu + u_{i,g})\delta + \epsilon_{i,g})$ or non-treatment

$(E_{i,g} = x_{i,g}\beta + \epsilon_{i,g})$ regime. For a more detailed description see for example

Cameron and Trivedi (2005, sec. 16.7 and 25.3.4) and Maddala (1983). We conduct the

estimation using full maximum likelihood under a normal distribution assumption.[29]

We do not claim that this approach resolves all potential selection/omitted variables bias

concerns, and it relies on assumptions about the correlation structure. Rather, we regard it

as a further useful robustness check to assess the sensitivity of our results to changes in the

econometric specification and the direction of selection-bias. The z_i in the selection equation

contains all variables in x_i, plus the variable "other criminals" which counts the number of

additional criminal candidates in the constituency in 2004. As reported above, other crimi-

nals did not pass the specification tests in IV regressions, but it provides plausibly exogenous

variation about the selection of a criminal candidate and could work satisfactorily here. We

run the regressions for all three dependent variables. Lamda is the inverse mills-ratio or non-

selection hazard, and the parameter rho indicates the correlation between the error terms ε_i

and u_i. We test the model assumption with a likelihood ratio test of an independent probit

and regression model versus the treatment effect likelihood, a test of rho=0 that is Chi-square

distributed. The test statistics rejects that rho equals zero for *attendance rate* and *MPLADS*

utilization, indicating that these models are valid. Other criminals is positive and significant

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[29] Alternatively we can regard this model as a non-standard Maximum likelihood estimator. The likelihood
function $L_N(\Theta) = f(y, X|\Theta) = f(y|X, \Theta)f(x|\Theta)$ generally would require specifying the conditional density
of y given X as well as the marginal density of X. It is standard to use only the conditional density $f(y|X, \Theta)$,
and ignore $f(X|\Theta)$. This in essence assumes exogenous sampling and conditional independence. Treatment
effects models drop this assumption, but instead assume a specific correlation structure of the error terms
of the two equations to be estimated.

in the selection equation as predicted (Appendix A4).

The results further support our earlier impression that not controlling for selection effects biases the OLS coefficient rather upwards than downwards. The negative relationship between criminal background and *attendance rates* becomes more negative and significant at the 1%-level. The same holds for the relation to *MPLADS utilization*: The coefficient of *Criminal(a)*, which was negative but insignificant in the baseline model, becomes larger in size and significant at the 1%-level.

The next rows omit potential extreme values or outliers in the earlier regression specifications in Tables 3 and 4. First, we omit the observations with the largest values of the respective dependent variable. Second, we calculate the residuals of the full regression, and omit the observations with the one-percent largest positive and negative residuals. The results for all dependent variables and both *Criminal(a)* and *Criminal(b)* are unaffected, indicating that the results are not driven by outliers or few observations.

Finally, we want to demonstrate how likely it is that, if all our prior robustness tests which suggest an upward bias failed, our results are explained by selection-on-unobservables. While our attempts so far suggest that selection, if anything, biases against the negative coefficient we measure, we cannot rule out that there are unobservable factors that lead to a problematic bias in the direction of our effect. Thus, we demonstrate with techniques developed in Altonji et al. (2005) how much larger on average selection bias on unobserved factors would have to be compared to selection on observed factors to fully explain our results.

The strategy is to use selection on observables to assess the severity of potential selection bias for the results. We compare two kinds of regressions: first, one without controls (U_1 = unrestricted) to one with our full set of controls (R=Restricted); and second, one with a limited set of controls for candidate characteristics (U_2) to one with full controls (R). We then calculated a "Selection ratio" (SR), which is the necessary ratio of selection on unobservables

to observables to fully explain our coefficients as $\hat{\beta}_R/(\hat{\beta}_U - \hat{\beta}_R)$. The denominator, i.e., the difference between the $\hat{\beta}$ coefficients indicates the degree to which our estimate is affected by selection on observables. A small difference indicates little selection effects. $\hat{\beta}_R$ in the nominator enters positively in the ratio, as we need stronger selection on unobservables to explain a larger coefficient. Altonji et al. (2005) provide the underlying assumptions and Bellows and Miguel (2008) a formal derivation.

We would argue that while our empirical proxies might in some cases not perfectly capture the theoretical parameters, they are overall very comprehensive and should at least be a useful guide to selection on observables. Altonji et al. (2005) posit that "there are strong reasons to expect the relationship between the unobservables and (...) generally any potentially endogenous treatment to be weaker than the relationship between the observables and dependent". The bottom part of Table 6 shows the respective ratios for $\hat{\beta}_R/(\hat{\beta}_{U1} - \hat{\beta}_R)$ and $\hat{\beta}_R/(\hat{\beta}_{U2} - \hat{\beta}_R)$, for our two limited sets (U_1) and (U_2). The results strongly confirm the negative relationship between criminal background and *attendance rates*: Selection on unobservables would have to be at least 3.7 - 5 [7 - 21] times as strong as selection on unobservables to fully explain the negative coefficient of *Criminal(a)* [*Criminal(b)*]. While we found no significant relationship between criminal background and *parliamentary activity*, we are interested in the ratio for *MPLADS utilization*. To explain the negative relationship between *Criminal*(b) and utilization rates, selection on unobservables would have to be about 3 times as high as on observables.

6   Concluding remarks

In this paper we examine whether the fact that a member of parliament has a criminal background influences his effort in the parliament and in developing his constituency. To be able to understand the implications of criminality on MP behavior, we developed a principal-agent model that illustrates the incentives faced by an elected MP with regard to his executed effort. The model incorporates voters' monitoring intensity with regard to a parliamentarian's effort, as well as the competitiveness and other characteristics of her constituency, to make

predictions about the effect of criminal background on individual effort. We show that it is not obvious that criminal MPs always exert less effort, but rather that differences crucially depend on the other parameters in the model.

The hypotheses derived from the PA-model are then put to an empirical test using data from the 14th Indian 2004 Lok Sabha election, and the subsequent 2004-2009 legislative period. While criminals in politics are a general issue, in India criminal MPs are a widespread phenomenon and widely regarded as a danger to the functioning of the world's largest democracy. This analysis was made possible by a judgment of the Indian Supreme Court in 2003 which asked every candidate to provide sworn affidavits that have to include details not only about their personal educational and financial particulars but also about their criminal background. We restrict our analysis to this legislative period because constituency boundaries were changed in the 2009 election. Thus, it is no longer possible to control for important constituency characteristics like the winning margins in previous elections.

We augment the existing literature, which has mostly focused on the initial decision of whether to field a criminal candidate in the first place Aidt et al. (2015) and on the connection of MP criminality with rather disjointed proxies for MP effort like final consumption in the respective district or constituency as in Chemin (2012) and luminosity as in Prakash et al. (2014). We provide a comprehensive direct assessment of effort by using three measures that each capture a slightly different facet of MP behavior. First, we use *attendance rates* (respectively absenteeism) as for example in Besley and Larcinese (2011), Gagliarducci et al. (2010, 2011), and Mocan and Altindag (2013). Second, we measure MPs' *parliamentary activity* based on the number of questions asked and their participation in debates (similar to Arnold et al., 2014 and Mocan and Altindag, 2013). Third, we follow Keefer and Khemani (2009) and use the utilization rate of the Member of Parliament Local Area Development Scheme (MPLADS) which offers several important advantages as a measure of effort on behalf of the MPs' respective constituencies. We use two proxies for criminal MPs, *Criminal(a)* for all MPs with a least one crime, *Criminal(b)* only for those with a least two charges.

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Our empirical results support the conclusions from our model, but also provide further interesting details. Focusing on the first measure, it seems to be the case that having a criminal background is generally related to higher absenteeism rates. This relation is robust to the inclusion of party and state fixed effects, as well as controls for electoral competition, monitoring intensity and candidate characteristics. On the other hand, results concerning the second measure indicate that there is no obvious correlation between *parliamentary activity* and criminal background. Our model has suggested that differences in effort levels between criminals and other MPs might be partly explained by the potential to extract rents or differences in monitoring intensity. Wealthier constituencies are more attractive for rent extraction and related to better monitoring, which led to the hypotheses that criminal MPs in rich constituencies work relatively more because they put more emphasis on their reelection prospects. This is exactly what the data show: The difference in effort between criminals and other MPs is particularly pronounced in poor constituencies and narrows in richer areas. Criminal background has a statistically significant negative relation with both *attendance rates* and *parliamentary activity* in less and medium developed constituencies.

With regard to making use of the MPLADS to develop their constituency, criminal background is also related to lower utilization rates. This coefficient is not significant for *Criminal(a)*, however, becomes statistically significant for *Criminal(b)*. This suggests that not all MPs with criminal charges necessarily form a homogenous group: there are some individuals who have been criminal only once or are falsely accused and those that repeatedly broke the law. For the latter it is much more likely that they still engage in criminal activities and can, for example, use bribes or voter intimidation to secure their reelection.

There are potential concerns as to whether our coefficients have a causal interpretation. Omitted variable bias, in our case mostly selection effects, might bias our coefficients. Based on our theoretical considerations, we argue that it is more likely that our point estimates are upwardly rather than downwardly biased. This assumption is supported by a series of robust-

ness checks. For the MPLADS variable, we follow Keefer and Khemani (2009) and run a series of falsification tests to see whether omitted variables like political or social fragmentation are responsible for our results. As expected, including these additional covariates separately or jointly leads to more negative coefficients. Moreover, the relationship is robust to controlling for the utilization rate in the period before, which should capture omitted constituency-specific variables. Specifically for *MPLADS utlization* we use selection on observables to demonstrate that the negative and significant coefficient for *Criminal(b)* constitutes an upper bound for the negative effect of criminal background on effort.

Similarly, we show in a series of more general robustness checks that the results using a matching estimator are quantitatively very similar to the OLS estimates, with on average slightly more negative coefficients. Moreover, the matching statistics suggest a good covariate balance across treatment and control group. Regressions omitting the most influential observations or potential outliers further support the baseline results. Criminal background on average results in higher abseentism and lower utilization rates. *Criminal(a)* relates to on average about 5% lower *attendance rates,* and *Criminal(b)* relates to about 7% lower utilization rates of the MPLADS program. We argue and explain why we think regression discontinuity and instrumental variable designs are invalid or at least not feasible alternatives. Instead we use endogenous binary-variable models that explicitly model the selection process, with the existence of other criminal candidates as an additional exogenous selection-variable. Finally, we draw on the seminal paper by Altonji et al. (2005), and demonstrate that our findings are unlikely to be caused solely by selection bias. Selection-on-unobservables would have to work partly contrary to selection on observables, and its effect would have to be 3 to 21 times stronger to fully explain our results.

Still, it is important to keep the limitations of our research design in mind and further explore this issue to provide additional evidence in future research. Credibility and trust in representatives is of crucial importance for the credibility of India's democracy. While transparency increases reporting of corruption events and corrupt officials (see Vadlamannati and Cooray

2014) and the provisioning of criminal information to voters should help them make informed choices, a large number of criminal candidates still make it to the parliament. Step by step, evidence shows that there seem to be detrimental consequences to criminals holding public office, and we hope that our study further helps to enhance transparency. Evidence regarding the interplay between criminal politicians holding public office and activity in parliament and development of constituencies is scarce and to the best of our knowledge did not exist for the case of India.

A   Appendix. A generalized model

In section 3, we assumed a specific functional relationship between political effort and the fraction of informed voters who end up voting for the incumbent. In this section, we relax this assumption. In the sequel, we use the following notation for partial derivatives: $\frac{\partial f}{\partial x} := f_x$ and $\frac{\partial^2 f}{\partial x \partial y} := f_{xy}$.

Again, consider two incumbents who differ only in the criminal characteristic. As before, the corresponding personal characteristics are denoted by x^c and x^n. Let $\mathcal{C}$ be the characteristic space (i.e. the space consisting of all possible characteristic combinations). In general, a function which represents the fraction of informed voters who end up voting for the incumbent needs to assign a share of voters (i.e. a number from the unit interval) to each characteristic vector $x \in \mathcal{C}$ and each effort level $e \in [0,1]$. Consider such a function $f(e,x)$ where $f : [0,1] \times \mathcal{C} \to [0,1]$. We assume that $f(e,x)$ is differentiable with respect to e, where $f_e > 0$ and $f_{ee} < 0$ for all $x \in \mathcal{C}$ (i.e. the marginal impact of effort on the share of voters is positive, but decreasing). Furthermore, empirical evidence indicates that voters penalize criminality (see section 3). Therefore, a criminal background as a characteristic feature decreases the marginal impact of effort on the fraction that is informed, $f_e(e,x^n) > f_e(e,x^c)$ for all $e \in [0,1]$. It seems plausible that the negative effect of a criminal background is weaker the higher the effort level, since a high effort level indicates good governance. Thus, the difference between marginal impacts of effort $\Delta^m := f_e(e,x^n) - f_e(e,x^c)$ is assumed to decrease in effort, $\Delta^m_e < 0$.

Assuming an interior solution, the first-order condition of optimization problem (1) of an incumbent with characteristic $x \in \mathcal{C}$ is

$$\frac{\iota}{(1-\iota)} \cdot \frac{1}{2(b-a)} \cdot U \cdot f_e(e, x) = 1 \tag{3}$$

where ι, U, a and b are defined as in section 3.

In the generalized model, the qualitative impact of ι, U and b on incumbent's optimal effort level are the same as in section 3:

Proposition 3. The optimal effort level of the incumbent is higher if

(i) voters are better informed (high ι)

(ii) the MP's utility from holding office is higher (high U)

(iii) the expected level of support is lower (low b)

Proof. Note that the optimal effort level of an incumbent with characteristic $x \in \mathcal{C}$ is implicitly given by equation (3). Consider the left-hand side of (3), $l(e, U, \iota, x) := \frac{\iota}{(1-\iota)} \cdot \frac{1}{2(b-a)} \cdot U \cdot f_e(e, x)$, and observe that $l_U, l_\iota > 0$ and $l_b < 0$. Now, recall that $sign(l_y) = sign(e_y^*)$ where $y \in \{\iota, U, b\}$ □

The next proposition examines the difference between the optimal effort levels of a a criminal and a non-criminal incumbent, e_c^* and e_n^*.

Proposition 4. The difference between optimal effort levels $\Delta_{e^*} = e_n^* - e_c^*$ is

(i) strictly positive

(ii) decreasing in ι

(iii) decreasing in U

Proof. (i) The optimal effort levels are implicitly given by (3). Equation (3) can be rewritten as $f_e(e, x) = z$ where $z \equiv \frac{(1-\iota)\cdot 2(b-a)}{\iota \cdot U}$. Thus, the optimal effort levels satisfy $f_e(e_n^*, x^n) = z = f_e(e_c^*, x^c)$. By assumption, it holds for all effort levels $f_e(e, x^n) > f_e(e, x^c)$, it follows that $e_n^* \neq e_c^*$. Since, furthermore, f_e is strictly monotone decreasing in e for all $x \in \mathcal{C}$, $f_e(e_n^*, x^n) = f_e(e_c^*, x^c)$ implies $e_c^* < e_n^*$. Hence, $\Delta_{e^*} > 0$. (ii) Proposition (3) shows that optimal effort levels are increasing in ι. At the same time, by assumption, the difference between marginal impacts of effort Δ^m decreases. Consequently, the difference Δ_{e^*} is decreasing in ι. Statement (iii) can be shown similarly. $\square$

In contrast to Proposition 2, (i) of Proposition 4 states that the optimal effort level of a non-criminal incumbent is strictly higher than that of a criminal. This is due to the assumption that the marginal impact of effort of a non-criminal on the fraction that is informed is strictly higher than that of a criminal. The "Tullock-function" in section 3 does not necessarily satisfy this property. For instance, take $m(x^c) = 1$ and $m(x^n) = 0.5$, then $I_e(\bar{e}, x^n) = I_e(\bar{e}, x^c)$ for $\bar{e} = 1/\sqrt{2}$. Furthermore, $I_e(e, x^n) > I_e(e, x^c)$ for all $e < \bar{e}$ and $I_e(e, x^n) < I_e(e, x^c)$ for all $e > \bar{e}$. However, results (ii) and (iii) of proposition 4 are also valid for functions $f(e, x)$ which satisfy this property (i.e. there exists a $\bar{e} \in (0, 1)$ such that $f_e(e, x^n) \geq f_e(e, x^c)$ for all $e \leq \bar{e}$ and $f_e(e, x^n) < f_e(e, x^c)$ for all $e > \bar{e}$). This can be shown by case distinction.

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Tables and Figures

Table 1: Descriptive statistics

	Count	Mean	SD	Min	Max	Mean - Normal	Mean - Criminal
Effort measure							
Attendance rate	394	1	0	0.06	0.96	0.73	0.67
Parliamentary activity	394	1	1	0.00	4.38	0.81	0.85
MPLADS utilization	439	106	20	60.50	260.00	106.02	104.45
Criminal Record	439						
Criminal(a)	439	0	0	0	1		
Criminal(b)	439	0	0	0	1		
Electoral competition							
Party stronghold (3time winner)	439	0	0	0	1	0.24	0.23
Margin (2004)	439	1	0	0	1	0.61	0.57
Voter turnout (2004)	439	10	1	6	12	9.80	9.71
Constituency characteristics							
Economic development (log sum of night light intensity)	439	55.69	12	25.86	85.43	56.05	54.55
Literacy rate	439	0.21	0	0.00	1.00	0.22	0.15
PC is reserved for minority SC or ST	439	0	0	0.00	0.61	0.13	0.11
No of voters	439	52	11	26.00	77.00	0.00	0.00
Candidate characteristics							
Candidate age (at election)	439	1.61	0.74	0.00	2.00	52.73	50.38
Formal education in 3 steps	439	1	1	0.00	3.00	1.64	1.50
Experience in parliament =no of times the MP has won before	439	1	0	0.00	1.00	0.77	0.55
Gender	439	16	1	1.61	20.33	0.92	0.94

Notes: Descriptive statistics were calculated for the maximum regression sample size.

Table 2: Criminals by party affiliation

	Normal		Criminal	
Bharatiya Janata Party	82	[78.8%]	22	[21.2%]
Communist Party of India (Marxist)	33	[82.5%]	7	[17.5%]
Indian National Congress	103	[84.4%]	19	[15.6%]
Rashtriya Janata Dal	11	[52.4%]	10	[47.6%]
Other	106	[69.7%]	46	[30.3%]
Total	335	[76.3%]	104	[23.7%]

Figure 2: Geographical distribution of candidates with criminal charges across constituencies for the 14th Lok Sabha.(after 2004 national election)
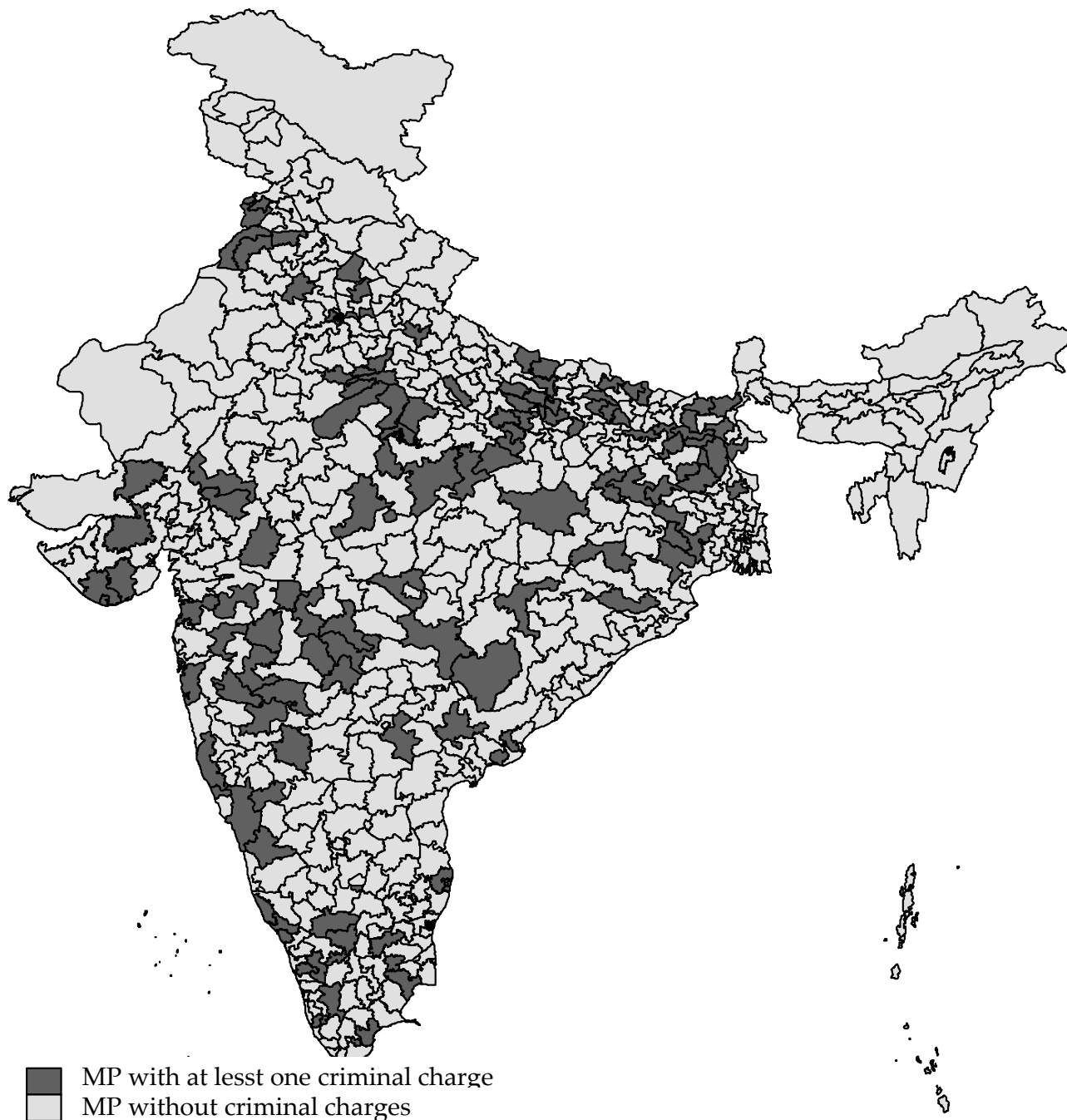

■ MP with at lesst one criminal charge
□ MP without criminal charges

Table 3: Main results for attendance rates and parliamentary activity

Dependent variable: Attendance rate	(1)		(2)		(3)		(4)	
Criminal(a)	**-0.046***	**[0.025]**	**-0.049****	**[0.022]**	**-0.050****	**[0.020]**	**-0.043***	**[0.023]**

Dependent variable: Parliamentary activity	(5)		(6)		(7)		(8)	
Criminal(a)	**0.002**	**[0.066]**	**-0.006**	**[0.065]**	**-0.003**	**[0.071]**	**-0.006**	**[0.075]**
Number of MPs	394		394		394		394	
State Dummies	Yes		Yes		Yes		Yes	
Party Dummies	No		Yes		Yes		Yes	
Electoral Competitiveness	No		Yes		Yes		Yes	
Monitoring Intensity	No		No		Yes		Yes	
Candidate Characteristics	No		No		No		Yes	

Dependent variable: Attendance rate	(9)		(10)		(11)		(12)	
Criminal(b)	**-0.126****	**[0.051]**	**-0.128*****	**[0.047]**	**-0.126*****	**[0.045]**	**-0.104****	**[0.045]**

Dependent variable: Parliamentary activity	(13)		(14)		(15)		(16)	
Criminal(b)	**-0.180**	**[0.160]**	**-0.181**	**[0.152]**	**-0.174**	**[0.156]**	**-0.150**	**[0.153]**
Number of MPs	394		394		394		394	
State Dummies	Yes		Yes		Yes		Yes	
Party Dummies	No		Yes		Yes		Yes	
Electoral Competitiveness	No		Yes		Yes		Yes	
Monitoring Intensity	No		No		Yes		Yes	
Candidate Characteristics	No		No		No		Yes	

Notes: Dependent variable as specified above over the full legislative period 2004-2009. Standard errors are clustered at the party level. Criminal(a) is defined as those having at least one criminal charge against them, Criminal(b) as those having more than one criminal charge against them. All regressions include the control variables as specified in Table 1 as indicated in the respective column. *** (**, *) indicates significance at the 1 (5, 10) percent level respectively.

Table 4: Interaction effects

Dependent variable: Attendance rate

Criminal(a)	-0.055***	[0.018]	-0.051**	[0.023]	-0.606***	[0.158]	-0.107	[0.117]
Interaction with:								
Party Stronghold	0.070	[0.065]						
Margin (2004)			0.077	[0.199]				
Economic Development					0.058***	[0.016]		
Literacy rate							0.001	[0.002]
Number of MPs	394		394		394		394	

Dependent variable: Parliamentary activity

Criminal(a)	0.035	[0.081]	0.029	[0.068]	-1.699***	[0.421]	0.12	[0.345]
Interaction with:								
Party Stronghold	-0.148	[0.111]						
Margin (2004)			-0.428	[0.744]				
Economic Development					0.194***	[0.058]		
Literacy rate							0.001	[0.008]
Number of MPs	392		392		392		392	

Notes: Dependent variable as specified above over the full legislative period 2004-2009. All regressions include all control variables as specified in table 1, including dummies for major states and parties. Criminal(a) is defined as those having at least one criminal charge against them. Standard errors [in brackets] are clustered at the party level. *** (**, *) indicates significance at the 1 (5, 10) percent level respectively.

Figure 1: Marginal Effect of *Criminal(a)* on *attendance rates* conditional on economic development
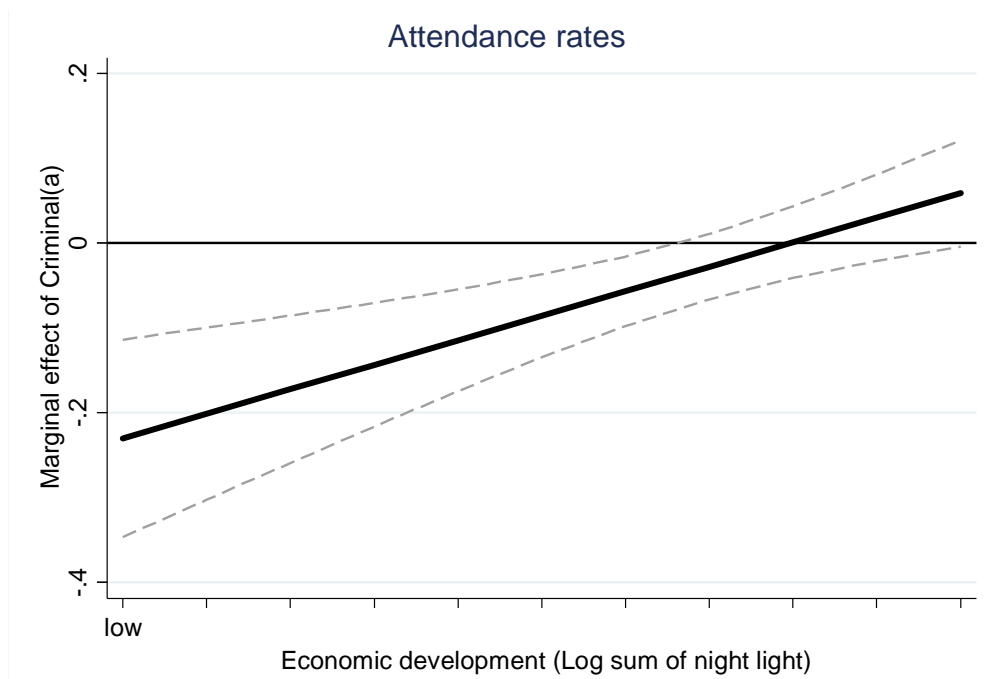
Notes: Marginal effect of Criminal(a) MP Dummy for different levels of economic development. Dotted lines represent the 95% confidence intervals.

Figure 2: Marginal Effect of *Criminal(a)* on *parliamentary activity* conditional on economic development
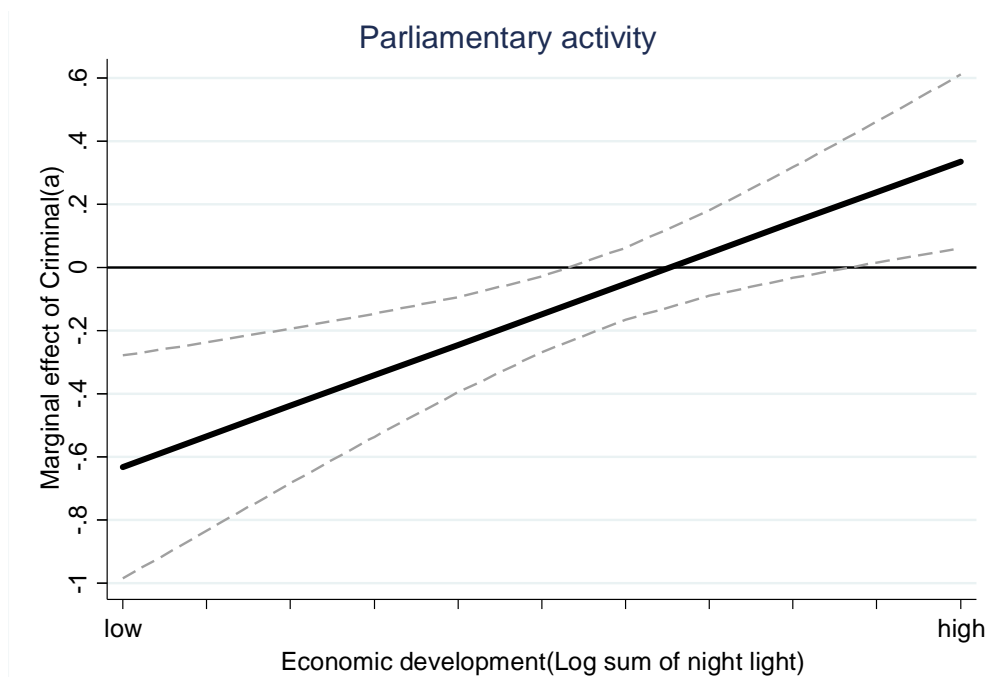
Notes: Marginal effect of Criminal(a) MP Dummy for different levels of economic development. Dotted lines represent the 95% confidence intervals.

Table 5.1: Main results for Member of Parliament Local Area Development Scheme (MPLADS) utilization

	(1)		(2)		(3)		(4)	
Criminal(a)	-3.014	[3.519]	-3.302	[3.563]	-3.273	[3.601]	-3.419	[3.733]
	(5)		(6)		(7)		(8)	
Criminal(b)	-7.083**	[2.677]	-7.372**	[3.005]	-7.042**	[3.106]	-7.723**	[3.415]
Number of MPs	439		439		439		439	
State dummies	Yes		Yes		Yes		No	
Party dummies	No		Yes		Yes		Yes	
Competition controls	No		Yes		Yes		Yes	
Monitoring controls	No		No		Yes		Yes	
Candidate characteristics	No		No		No		Yes	

Table 5.2: Robustness tests (based on column 4)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criminal(b)	Coef.	-7.793*	-7.658**	-7.479**	-9.664**	-7.679**	-7.643**	-5.642*	-8.541**
Additional controls for	SE	[4.050]	[3.554]	[3.355]	[3.482]	[3.529]	[3.506]	[3.015]	[3.676]
Development fund utilization (1999-2004)		Yes					Yes		
Leftover funds from predecessor			Yes				Yes		
Political fragmentation 1991- 1999				Yes			Yes		
Caste and religious fragmentation					Yes		Yes		
Electoral volatility						Yes	Yes		
Sensitivity analysis									
Omit 10 constituencies with highest utilization rates								Yes	
Only Criminal(b) vs. Non-Criminals									Yes

Notes: Robustness checks. Dependent variable is the cumulative utilization rate over the 2006-2008 period (Check). Criminal(a) is defined as those having at least one criminal charge against them, Criminal(b) as those having more than one criminal charge against them. All regressions include the control variables as specified in Table 1 as indicated in the respective column. Standard errors [in brackets] are clustered at the state level. *** (**, *) indicates significance at the 1 (5, 10) percent level respectively.

Table 6: Robustness checks for all dependent variables

Dependent variable	Attendance rate		Parliamentary activity		MPLADS utilization	
Baseline results	Coef.	SE	Coef.	SE	Coef.	SE
Criminal(a)	-0.043*	[0.023]	-0.006	[0.075]	-3.419	[3.733]
Criminal(b)	-0.104**	[0.045]	-0.150	[0.153]	-7.723**	[3.415]
	Matching estimator (nearest neighbor matching)					
Criminal(a) & NN (2)	-0.061***	[0.023]	-0.048	[0.136]	-7.077**	[3.283]
Criminal(a) & NN (3)	-0.054**	[0.022]	0.003	[0.125]	-4.291	[2.865]
Criminal(b) & NN (2)	-0.135***	[0.046]	-0.317	[0.205]	-18.169***	[6.095]
Criminal(b) & NN (3)	-0.135***	[0.043]	-0.331	[0.208]	-12.222***	[4.642]
	Treatment effect estimator					
Criminal(a)	-0.187***	[0.069]	-0.211	[0.172]	-10.659***	[3.655]
Lamda	0.09		0.12		4.28	
Rho	0.57		0.16		0.22	
Prob > Chi^2	0.0744		0.1183		0.004	
Regressions	*w/o 2% largest values of dependent variables*					
Criminal(a)	-0.046*	[0.024]	0.005	[0.072]	-2.155	[2.792]
Criminal(b)	-0.101**	[0.045]	-0.034	[0.086]	-5.699*	[2.907]
	w/o 1% largest positive and negative residuals					
Criminal(a)	-0.042*	[0.022]	-0.034	[0.086]	-3.472	[2.811]
Criminal(b)	-0.113**	[0.042]	-0.137	[0.136]	-6.666**	[3.138]
	Using selection-on-observables to assess the bias from unobservables					
Controls (Restricted/ Full))	Selection ratio SR=ß$_R$/(ß$_U$-ß$_R$)					
Criminal(a)						
None (U$_1$) / Full controls (R)	3.68		0.14		1.84	
Candidate Characteristics (U$_2$) / Full controls (R)	5.10		0.13		2.02	
Criminal(b)						
None (U$_1$) / Full controls (R)	6.98		1.14		2.92	
Candidate Characteristics (U$_2$) / Full controls (R)	21.13		0.91		3.19	

Notes: Matching was conducted on all variables that acted as controls in the prior regressions, including party and state dummies. The appendix shows balance statistics.

The treatment effect regressions are estimated using maximum likelihood. In the first row, selection is based on on all constituency characteristics from the baseline model.

For the regression in the bottom part, we first calculated the baseline regression. Then we calculated the observations with the largest residuals and omitted them from the regressions.

Appendix B (Supposedly online appendix in published version)

ATab 1: Criminals by state

State\ Status	Normal		Criminal(a)			Normal		Criminal(a)	
Andaman Nicobar	1	[100.0%]	0	[0.0%]	Maharashtra	21	[53.8%]	18	[46.2%]
Andhra Pradesh	29	[90.6%]	3	[9.4%]	Manipur	2	[100.0%]	0	[0.0%]
Arunachal Pradesh	2	[100.0%]	0	[0.0%]	Meghalaya	1	[100.0%]	0	[0.0%]
Assam	14	[100.0%]	0	[0.0%]	Mizoram	1	[100.0%]	0	[0.0%]
Bihar	19	[61.3%]	12	[38.7%]	NCT of Delhi	3	[60.0%]	2	[40.0%]
Chhattisgarh	6	[75.0%]	2	[25.0%]	Nagaland	1	[100.0%]	0	[0.0%]
Dadra & Nagar Haveli	1	[100.0%]	0	[0.0%]	Orrisa	16	[84.2%]	3	[15.8%]
Daman & Diu	0	[0.0%]	1	[100.0%]	Pondicherry	1	[100.0%]	0	[0.0%]
Goa	1	[100.0%]	0	[0.0%]	Punjab	7	[63.6%]	4	[36.4%]
Gujarat	17	[73.9%]	6	[26.1%]	Rajasthan	20	[87.0%]	3	[13.0%]
Haryana	7	[87.5%]	1	[12.5%]	Sikkim	1	[100.0%]	0	[0.0%]
Himachal Pradesh	3	[100.0%]	0	[0.0%]	Tamil Nadu	28	[75.7%]	9	[24.3%]
Jammu & Kashmir	4	[100.0%]	0	[0.0%]	Tripura	2	[100.0%]	0	[0.0%]
Jharkhand	4	[44.4%]	5	[55.6%]	Uttar Pradesh	46	[74.2%]	16	[25.8%]
Karnataka	15	[75.0%]	5	[25.0%]	Uttaranchal	3	[100.0%]	0	[0.0%]
Kerela	12	[63.2%]	7	[36.8%]	West Bengal	34	[94.4%]	2	[5.6%]
Madhya Pradesh	13	[72.2%]	5	[27.8%]	Total	335	[76.3%]	104	[23.7%]

ATab 2: Baseline results

|	Attendance rate		Parliamentary activity		MPLADS utilization	
	(1)		(2)		(3)	
Bharatiya Janata Party	-0.003	[0.013]	-0.097	[0.116]	-2.033	[2.010]
Communist Party of India	0.063	[0.039]	-0.373**	[0.156]	5.680	[4.190]
Indian National Congress	0.054***	[0.014]	-0.128	[0.104]	-3.784*	[2.110]
Rashtriya Janata Dal	0.026	[0.018]	0.288**	[0.123]	-4.187	[3.545]
Samajwadi Party	0.074**	[0.028]	0.160*	[0.087]	-4.052	[2.733]
PC reserved for minority	0.058***	[0.013]	-0.104	[0.100]	-2.100	[2.388]
Party stronghold (3time winner)	0.031	[0.031]	0.024	[0.154]	0.929	[2.552]
Winning margin (2004)	-0.175*	[0.094]	-0.539	[0.333]	-5.665	[6.516]
Voter turnout (2004)	-0.232***	[0.076]	-0.381	[0.634]	-15.162	[10.951]
Economic development	-0.011	[0.015]	0.101*	[0.057]	0.479	[1.430]
Literacy rate	0.002***	[0.001]	0.003	[0.003]	0.143	[0.114]
Candidate age (at election)	0.003***	[0.001]	0.000	[0.003]	0.008	[0.109]
Formal education in 3 steps	0.024***	[0.007]	0.046	[0.070]	0.289	[1.663]
Experience in parliament	-0.013	[0.012]	0.018	[0.040]	-1.250	[1.119]
Gender	-0.014	[0.032]	0.207*	[0.105]	-0.305	[3.962]
Net assets (log)	-0.019**	[0.008]	-0.001	[0.032]	-0.362	[0.457]
R-Squared	0.29		0.11		0.08	
Number of MPs	394		394		439	
State Dummies	Yes		Yes		Yes	

Notes: Dependent variable as specified above over the full legislative period 2004-2009, MPLADS 2005-2008. Standard errors are clustered at the party level. *** (**, *) indicates significance at the 1 (5, 10) percent level respectively.

AFigure 1: Example of the affidavits that were used for coding the criminal variable
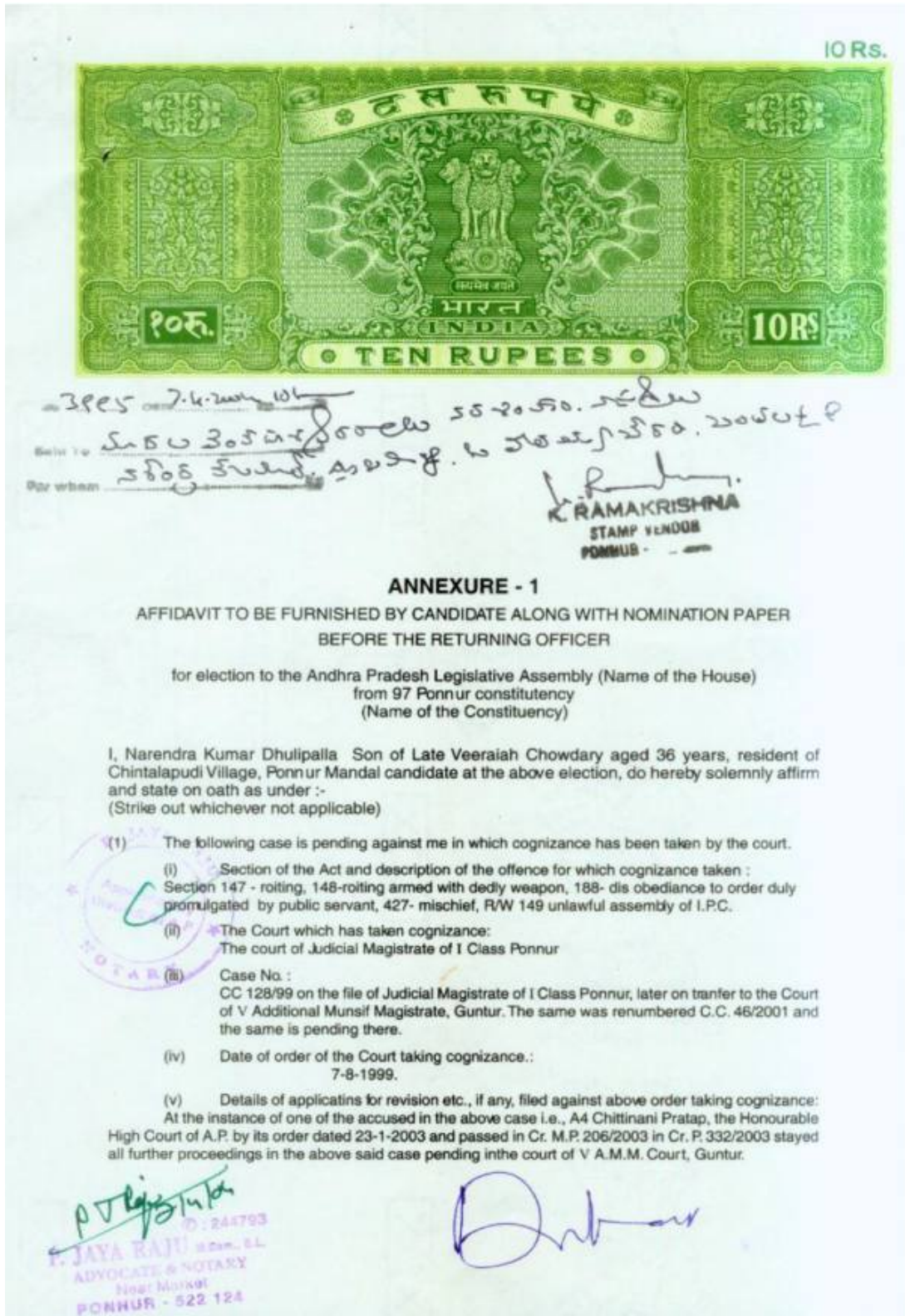
AFigure 2: Constituency-level approximation of economic development based on nighttime light intensity using satellite data.
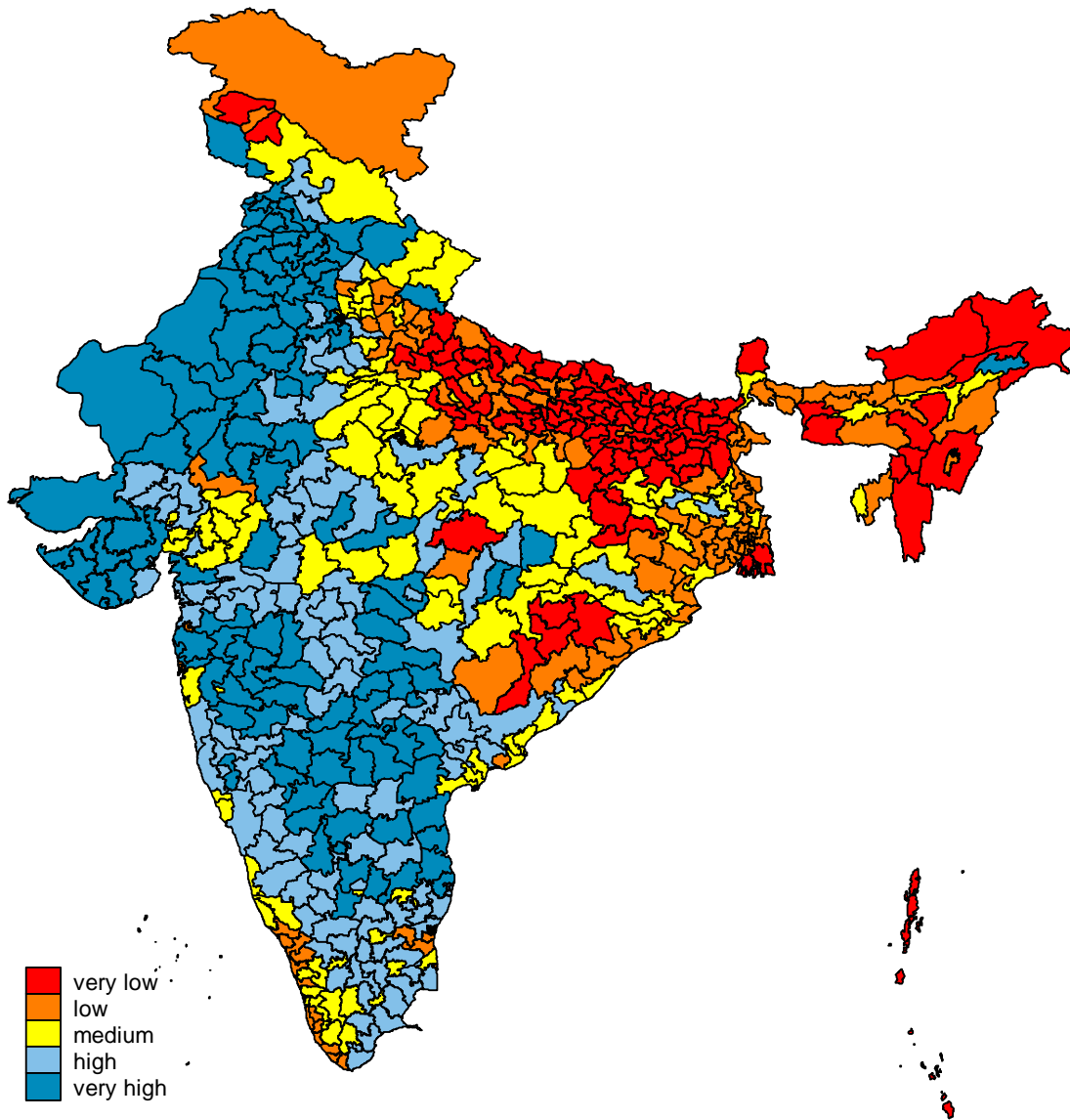
Notes: Created using average visible, stable light and cloud free from the F16 satellite for 2004. The original description states that "The cleaned up (file) contains the lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded. Then the background noise was identified and replaced with values of zero. Data values range from 1-63. Areas with zero cloud-free observations are represented by the value 255." More information can be found at http://ngdc.noaa.gov/eog/gcv4_readme.txt. We use the tif-image-file from the National Geophysical Data Center and merged it in ArcGIS with constituency boundaries that were shared by Aidt et al. (2015). We then calculated the sum of lights using zonal statistics within the constituencies to proxy for economic development.

AFigure 3: Violinplots of dependent variables
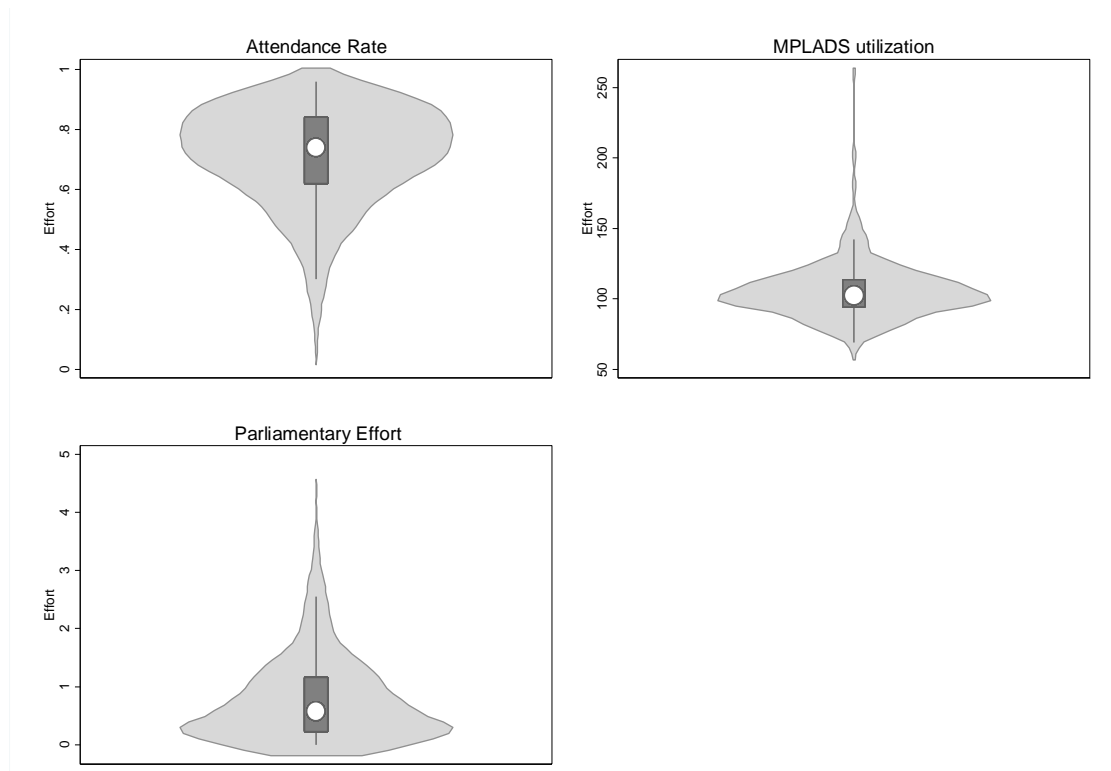
Notes: Violin plots are a modification of box plots that add plots of the estimated kernel density to the summary statistics displayed by box plots. The white dot indicates the median value, the box comprises the 25th to 75th percentiles. Points beyond the upper and lower adjacent values indicate potential outliers.

ATab 3: Frequency of Crimes

Number of Crimes	Frequency	Percentage	Specification 1	Specification 2	Specification 3
0	336	[76.54%]	Non-Criminals	Non-Criminals	Non-Criminals
1	54	[12.30%]			Excluded
2	20	[4.56%]			
3	8	[1.82%]			
4	7	[1.59%]			
5	3	[0.68%]	Criminal(a)	Criminal(b)	Criminal(b)
8	1	[0.23%]			
9	1	[0.23%]			
13	3	[0.68%]			
18	1	[0.23%]			

Notes: Specification 1 is the main specification, used for example in Table 3, column 1-3. Specification 2 is used in all specifications using Criminal(b), for example Table 3, column 4-6. The one exception is the last row in Table 5.2, where Specification 3 is used as a robustness check.

Descriptive statistics for the matching specifications:

ATab 4: Descriptive statistics for treated and control group

	Mean			t-test	
Variable	Treated	Control	%bias	t	p>t
PC reserved for minority	0.25	0.19	14.7	1.05	0.297
Party stronghold (3time winner)	0.17	0.13	9.7	0.74	0.458
Winning margin (2004)	0.10	0.09	12.9	1.06	0.288
Voter turnout (2004)	0.57	0.57	-5	-0.38	0.704
GDP (sum of night lights)	9.70	9.71	-1.6	-0.11	0.914
Literacy rate	54.79	56.23	-11.5	-0.73	0.464
Candidate age (at election)	49.85	51.23	-13.4	-0.96	0.34
Formal education in 3 steps	1.48	1.70	-27.9	-2.05	0.041
Experience in parliament	0.56	0.58	-2.4	-0.18	0.858
Gender	0.96	0.98	-7.3	-0.67	0.503
Log of net assets	16.05	16.12	-6.8	-0.61	0.541

Notes: Relates to Table 6. T-test is a simple t-test of differences in the mean. Outcome variable is *attendance rate*.

AFigure 4: Matching balance
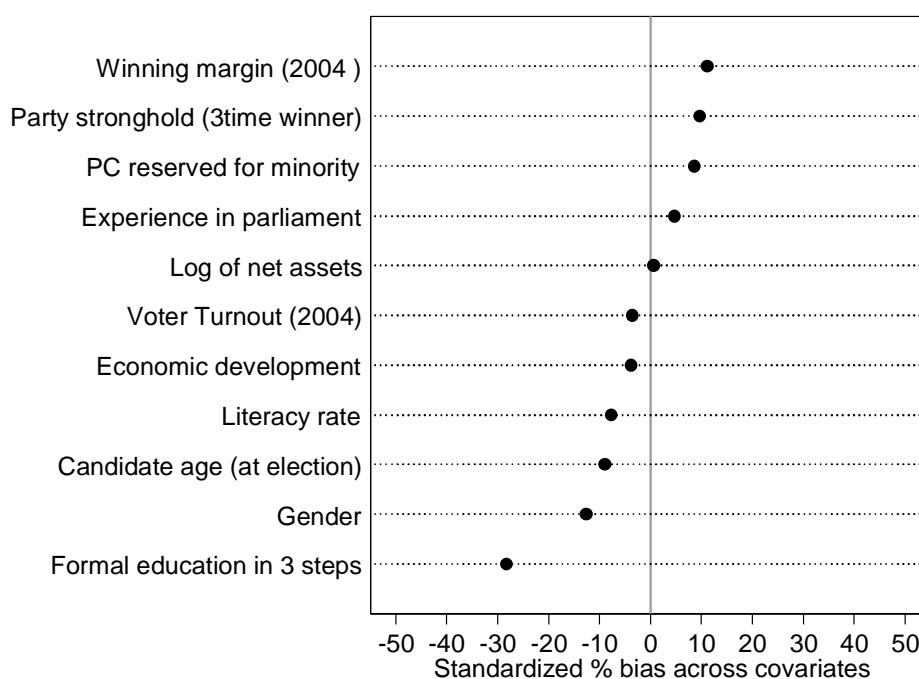
Notes: Relates to Table 6. Graphical depiction of matching balance. Results remain qualitatively unchanged when matching exactly on education.

ATab 5: Selection equations for treatment effect regressions

Dependent variable in second stage	Attendance rate		Parliamentary activity		MPLADS	
Dependent variable in selection equation	Criminal(a)		Criminal(a)		Criminal(a)	
Criminal(a)	**-0.578****	**[0.229]**	**-0.559****	**[0.239]**	**-0.513**	**[0.349]**
Bharatiya Janata Party	0.081	[0.384]	0.031	[0.404]	0.095	[0.439]
Communist Party of India	-0.354**	[0.155]	-0.380**	[0.167]	-0.472	[0.311]
Indian National Congress	0.359	[0.430]	0.359	[0.418]	0.568***	[0.209]
Rashtriya Janata Dal	0.147	[0.186]	-0.021	[0.142]	0.017	[0.154]
Samajwadi Party	0.064	[0.218]	0.081	[0.236]	0.014	[0.166]
PC reserved for minority	-1.561	[1.506]	-1.749	[1.642]	-1.552	[1.027]
Voter Turnout (2004)	-0.061	[0.114]	-0.008	[0.106]	0.009	[0.117]
GDP (log sum of night lights)	-0.018*	[0.009]	-0.018**	[0.009]	-0.023*	[0.014]
Literacy rate	-0.004	[0.302]	0.003	[0.272]	-0.091	[0.250]
Party Stronghold (3time winner)	-0.083	[0.907]	0.103	[0.793]	0.347	[0.729]
Margin (2004)	-0.014***	[0.005]	-0.012**	[0.005]	-0.012	[0.009]
Candidate Age (at election)	-0.142***	[0.048]	-0.153***	[0.053]	-0.186*	[0.097]
Formal Education in 3 steps	-0.102	[0.062]	-0.088	[0.058]	-0.094	[0.067]
Experience in parliament	0.579	[0.352]	0.523	[0.336]	0.294	[0.299]
Gender	0.048	[0.095]	-0.010	[0.027]	0.012	[0.051]
Number of other contesting candidates with charges	0.168**	[0.083]	0.207**	[0.100]	0.152*	[0.092]
State Dummies	Yes		Yes		Yes	
SE's clustered at	State level		State level		State level	
Number of MPs	394		394		439	
Lamda	0.09		0.12		4.28	
Rho	0.57		0.16		0.22	
Prob>Chi2	0.0744		0.1183		0.004	

Notes: Dependent variable as specified above over the full legislative period 2004-2009, MPLADS 2005-2008.

Second stage results for *Criminal(a)* see Table 6. Standard errors are clustered at the party level. *** (**, *) indicates significance at the 1 (5, 10) percent level respectively.

ATab 6: Relation between dropping out of sample, dependent variable and variable of interest

Dependent variable

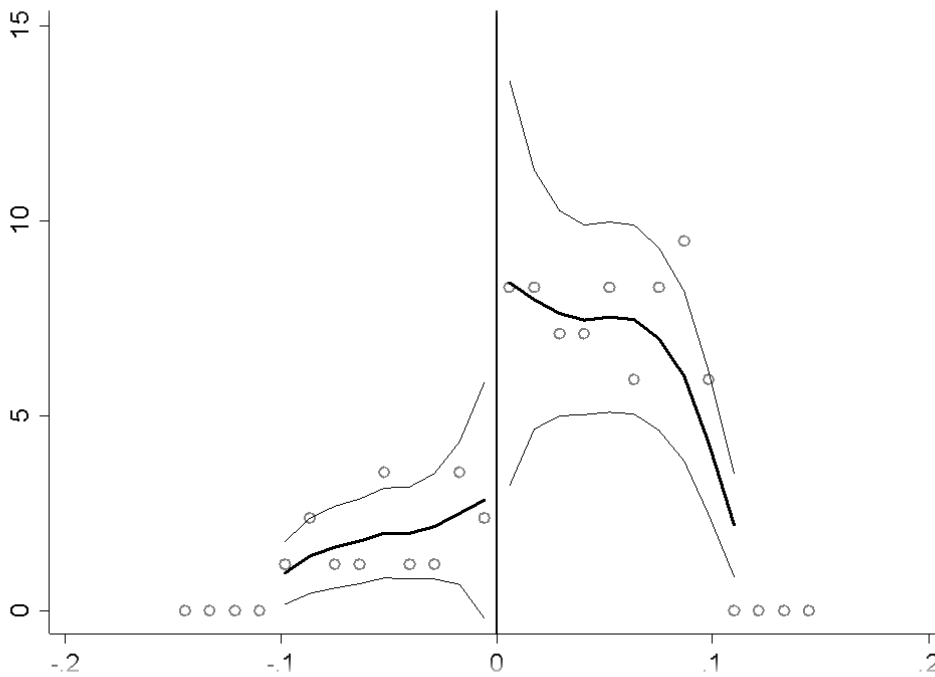|	Criminal Winner(a)		MPLADS	
MP change from MP data	0.005	[0.048]	1.843	[2.508]
Bharatiya Janata Party	-0.087	[0.064]	1.018	[3.307]
Communist Party of India (Marxist)	-0.032	[0.099]	8.582*	[5.102]
Indian National Congress	-0.078	[0.056]	-2.720	[2.906]
Rashtriya Janata Dal	0.137	[0.127]	-2.731	[6.573]
Samajwadi Party	0.006	[0.095]	-3.243	[4.904]
Reserved seat (SC or ST)	-0.039	[0.046]	-1.774	[2.375]
Voter turnout (2004)	-0.216	[0.246]	-18.810	[12.743]
No of voters	-0.005	[0.028]	-0.798	[1.446]
Party Stronghold (3time winner)	-0.004	[0.002]	0.285**	[0.125]
Party Stronghold	-0.028	[0.060]	4.401	[3.112]
Margin (2004)	0.006	[0.201]	-12.334	[10.428]
Economic Development	-0.003*	[0.002]	0.039	[0.089]
Candidate Age (at election)	-0.042*	[0.025]	1.243	[1.273]
Formal Education in 3 steps	-0.009	[0.021]	-2.213**	[1.110]
Experience in parliament	0.090	[0.069]	-1.722	[3.574]
Gender	0.009	[0.018]	0.193	[0.907]
Log of net assets	-0.039	[0.046]	-1.774	[2.375]
Adjusted R-Squared	0.06		0.03	
Number of constituencies	540		540	
SE's clustered at	State level		State level	

Notes: Analyzes whether there is a relation between *Criminal(a)* and MP's dropping out of parliament, and between the dependent variable *MPLADS utilization* and MP's dropping out of parliament. Standard errors are clustered at the state level. If *Criminal(a)* would be significantly related to the change, this could bias our results. If it would be significantly related to our dependent variables, it would be an omitted variable bias problem. We are only able to capture the value of the dependent variable for those constituencies with a change during the term. Abseentism and Parliamentary activity are not provided for those constituencies with a change in MP. We can see in both regressions that there is no significant relationship; hence this does not affect our results.

A Figure 5: Validity of Regression discontinuity assumptions – Density around the threshold
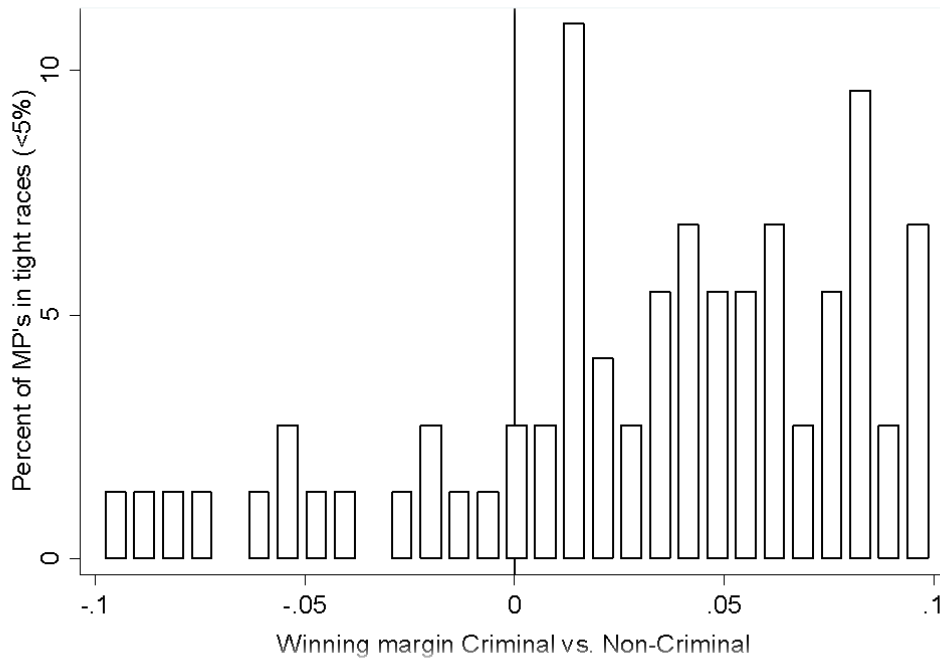
Notes: This suggests that criminals are able to manipulate elections. This seems to hold for the close elections with a winning margin +/- 10%.

A Figure 6: McCrary test

Notes: Density graph based on the DCdensity program code from http://eml.berkeley.edu/~jmccrary/DCdensity/. The x-axis display the margin between a criminal winner and a non-criminal runner-up in close elections with a winning margin +/-10%.