# Manipulating the System: Clientelism and Criminality in Politics *

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Job Market Paper

**Abstract**

Why do criminal politicians win elections? Scholars theorize that voters may forgive criminal allegations when politicians are more effective at delivering state resources. This paper examines this theory with data from India's largest rural workforce program. Using a regression discontinuity design, I find that in constituencies where a criminal politician won, the project completion rate falls by 68%, but work allocation increases by 36%. Program funds in criminal constituencies are disproportionately allocated to labour, rather than materials. These findings suggest that criminal politicians strategically target the wage dimension of the program as a mechanism to buy voter support.

**JEL Classification**: D72, D73, H41, H53, O12

**Keywords**: Criminal Politicians, Clientelism, Regression Discontinuity, Antipoverty Programs, India

*I would like to thank Pranab Bardhan, Simon Chauchard, Pradeep K. Chhibber, Francesca R. Jensenius, Jordi Munõz, Hannes Mueller, Ben Olken, Pavithra Suryanaryan, Pilar Sorribas-Navarro, Pau Vall-Prat, and Milan Vaishnav for their helpful comments. I am also grateful to the participants at the UB School of Economics Seminar, European Economic Association Summer Meeting 2023, Spanish Economic Association Meeting 2023, European Public Choice Society Meeting 2024, 2nd European Meeting on the Political Economy of South Asia, and European Political Science Association Annual Conference 2024 for their valuable comments and feedback. This work was supported by the Spanish Ministry of Science, Innovation and Education [PID2021-126517NB-I00].

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# 1 Introduction

The electoral success of low-quality politicians is often associated with having adverse effects on the distribution of resources and overall economic activity (Besley, 2006; Caselli and Morelli, 2004). However, citizens around the world are often complicit in supporting candidates of disrepute. Why do voters despite having the option to do so, fail to "throw the rascals out"?

A dominant argument often made is that this is purely an information constraint problem. This explanation holds that voters generally have a distaste for venal candidates but do not punish them simply because they lack the awareness to do so (Ferraz and Finan, 2008; Winters and Weitz-Shapiro, 2013). However, recent evidence suggests that even when voters receive credible information on the criminal activities of candidates, they show a willingness to support them (Banerjee et al., 2011; Boas et al., 2019).

A counterargument to the information hypothesis is that voters might be more prone to forgive probity if there are direct benefits on offer (Manzetti and Wilson, 2007). In other words, citizens might be making a strategic decision to support criminal politicians if they are more effective at providing them with better access to public goods. This lack of voter response to bad quality legislators can be most prominent in countries that exhibit weak government institutions and the state cannot fulfill its basic responsibilities, allowing clientelism to prosper (Easterly and Levine, 1997; Stokes, 2005). In such an environment, criminal politicians can take control of state resources and use their delivery as a mechanism to buy voter support.

While there is some literature linking corruption or criminality with clientelism (Manzetti and Wilson, 2007; Vaishnav, 2017), existing research shows that the electoral success of low-quality legislators is often associated with adverse effects on various components of the economy, such as household consumption and private investment (Chemin, 2012; Nanda and Pareek, 2016), economic development (Prakash et al., 2019), and government trust (Solé-Ollé and Sorribas-Navarro, 2018). I argue that despite the detrimental effects corrupt or criminal politicians have on long-term growth, these same politicians might be more effective in providing certain resources to their constituents. In particular, to gain an electoral advantage, criminal politicians leverage their reputation and access to wealth to strategically deliver targeted benefits that they can claim credit for and voters might care more about. By doing so, they can convey that criminality serves as a positive signal of competence and this is why voters might support them.

To test this theory, I examine the effects of electing criminal politicians on the delivery of one of India's largest government programs, the Mahatma Gandhi

National Rural Employment Guarantee Act (MGNREGA). MGNREGA is India's largest anti-poverty social program aimed at providing rural households with 100 guaranteed working days at a basic minimum wage. In addition to generating employment, the program aims to improve village infrastructure (e.g., roads, toilets, and canals).

The Indian case provides an ideal setting to examine this hypothesis for several reasons. First, despite holding massive free democratic elections with multiple parties, politicians accused of criminality are frequently elected at all levels of government. For example, in the last concluded *Lok Sabha* (national) elections of 2019, 43% of the Members of Parliament faced criminal accusations against them, up from 34% in 2014 and 30% in 2004.[1] Second, since the availability of resources is limited and often heavily mediated by middlemen, India is a potential scenario for clientelistic networks to thrive.

I take advantage of the Indian Supreme Court judgment in 2003, mandating all political candidates contesting in Indian elections to submit an affidavit disclosing information on their criminal background. Leveraging the data from these affidavits, I test if the election of a Member of the Legislative Assembly (MLA) with a criminal record impacts the delivery of MGNREGA on two main outcomes: number of projects completed ("Projects Completed") and number of days worked ("Work Days") annually. In particular, I test the effect of electing a criminally accused politician in MGNREGA in the state of West Bengal during the 2011 to 2020 period. I focus on West Bengal because it is one of the better performing states in terms of allotting jobs and utilizing funds under the scheme.[2] The program often suffers from implementation issues that can lead to substantial variation in access across Indian states.[3] Thus, using data from West Bengal ensures that the estimates in this paper are at the lower bound.

An important challenge in estimating the impact of criminal politicians on policy outcomes is that it is highly unlikely that the selection of an MLA with a criminal record is random. For example, criminal candidates might be more likely to run and be elected to office from certain constituencies over others. Thus, constituencies that elect a criminal politician may not be comparable to those that elect a non-

[1] The data on candidates' criminal records is collected from MyNeta, an open data platform run by the Association for Democratic Reform (ADR). Retrieved from https://myneta.info

[2] The Hindu (2018). "Bengal tops in rural job scheme, T.N. is second". Retrieved from https://www.thehindu.com/news/national/bengal-tops-in-rural-job-scheme-tn-issecond/article23041918.ece

[3] For example, certain states commonly perform better, while others lag behind (e.g., poorer states like Bihar, Uttar Pradesh, and Jharkhand) This variation is a result of low bureaucratic and fiscal capacity that can often lead to higher leakages in the program (Imbert and Papp, 2015; Muralidharan et al., 2016).

criminal. To overcome this endogeneity problem, I use a regression discontinuity (RD) design, comparing constituencies where a criminal candidate barely won to constituencies where they barely lost. Given the close margin of victory, the success of criminal candidates in these constituencies should be close to random (Lee and Lemieux, 2010). I find that criminal politicians have substantial effects on the delivery of MGNREGA. The election of a criminal politician leads to an annual decrease in the number of Projects Completed by 68% and an increase in the work allocation by 36% relative to the mean value of the dependent variable. I further find that this effect is more pronounced for legislators who run for re-elections in the subsequent election cycle, are accused of serious criminal allegations, and contest from non-reserved constituencies. These results suggest that criminal politicians are more inclined to deliver government benefits to their constituents when there are potential electoral benefits on offer.

Next, I explore whether these results are driven by some underlying rent-seeking activities. For this purpose, I construct various measurements that might be indicative of corruption and find no robust evidence that corruption is a potential mechanism. Instead, I find that criminal politicians spend a larger portion of the funds on the labor component of the program rather than on the materials. Since material expenditure is often the portion that provides opportunities to engage in rent-seeking (Afridi and Iversen, 2013; Das and Maiorano, 2019), these results suggest that criminal politicians systematically target the wage dimension of the program as a tool to connect with their voters.

This paper makes several contributions to the existing literature. Foremost, this paper contributes to the ever-growing literature trying to explain why voters elect bad-quality legislators in democratic countries. The existing literature provides several explanations for this surprising voter behavior, such as lack of adequate information (Ferraz and Finan, 2008), ethnic voting (Banerjee and Pande, 2007), patronage voting (Kitschelt and Wilkinson, 2007), and vote buying (Bratton, 2008). These theories rely on the assumption that criminality is an undesirable quality, and these factors play a mitigating effect. My findings reveal that voters might rationally reward such politicians because they believe this to be a necessary trait in politics.

Second, this paper contributes to the broader literature on distributive politics. The findings of this paper are difficult to reconcile with the standard models of distributive politics, such as elite capture theories. For example, Anderson et al. (2015) finds that landlord elites in Indian villages impede the implementation of pro-poor policies to keep labor compliant and wages low. In return, they gain control over village politics by offering social insurance to the poor majority, leading to elite capture through clientelistic trading. Several other studies show that vote buying is often negatively correlated with public goods provision (Acemoglu et al., 2014; Blattman et al., 2019). In contrast, the results of this paper can be explained by political clientelism that can significantly differ from elite capture. Bardhan and Mookherjee (2012) theorize that politicians often target the poor to gain voter support by providing short-term public goods. This can give the appearance of successful implementation of pro-poor programs, but often comes at the expense of providing long-term public goods. This pattern of using clientelistic strategies can be found in several case studies in which politicians distribute targeted public resources to consolidate political power (Kitschelt and Wilkinson, 2007; Stokes et al., 2013). This paper adds to this literature by providing evidence showing how criminal politicians can use clientelism as an effective tool to maintain public support.

Third, more narrowly, the results in this paper bridge the gap between the two competing strands of literature in India: one that uses qualitative fieldwork argues that criminal politicians might be more adequate to "get things done" (Martin and Michelutti, 2017; Vaishnav, 2017), and the other that finds that criminal politicians have adverse effects on overall economic welfare (Chemin, 2012; Prakash et al., 2019). I find that despite the reduction in overall program efficiency, the election of a criminal politician can have a positive effect on specific policy outcomes. This might explain why voters perceive such politicians to be competent and vote for them on the ballot. Lastly, while this paper concentrates on the Indian case, criminal politicians are not limited to India.[4] Thus, these findings might be of relevance to various developing countries that are struggling with similar situations.

The rest of the article is structured as follows: Section 2 provides a theoretical discussion of why criminal politicians might be better at providing better access to government schemes. Sections 3 and 4 discuss the background of MGNREGA and the electoral context, respectively. Section 5 describes the data. Section 6 introduces the empirical strategy. Section 7 presents the validity of the RD design, the results, and its robustness. Section 8 provides some policy implications and concludes.

## 2 Criminal Politicians and Public Goods Provision

The electoral success of criminal politicians is often associated with having detrimental effects on economic welfare and democratic functioning. Yet, such politicians are regularly elected to public office, despite this reputation. In this paper, I argue that the election of criminal politicians might not always lead to adverse effects. When electorally motivated, these same politicians can use their criminal networks and reputation to move the bureaucratic wheel, diverting resources to

[4] Several developing countries have reported a rise in criminal politicians being elected to office, such as (but not limited to) Brazil, Indonesia, Pakistan, the Philippines, and Nepal.

their constituents. Under such conditions, if criminal politicians are more effective in providing targeted benefits, citizens might be willing to support them, even if they are criminals.

The argument I propose has several theoretical and empirical foundations. Several studies have shown that politicians are willing to engage in distributive politics to garner voter support. Aidt and Shvets (2012) find that in the United States senators seeking re-election are willing to bring the "pork" home, despite amplifying the common pool problem. Scholars have argued that this behavior of legislators acting solely based on their parochial interests can be most prevalent in countries that have limited state capacity and the formal state is unable to meet the basic needs of citizens (Manzetti and Wilson, 2007; Stokes, 2005). Such conditions allow corrupt politicians to step in and gain control over state resources and, in turn, use the delivery of public goods as a mechanism to buy votes. Since access to public goods in such societies is scarce, citizens are willing to exchange votes for any resources that might be on offer. This makes clientelism a winning electoral strategy in the hands of corrupt or criminal politicians.

India provides a potential scenario for such clientelistic networks to thrive, since access to resources is often heavily mediated with corrupt actors and government institutions are weak. For example, Vaishnav (2017) in his seminal work on understanding the nexus between criminals and politics in India, theorizes that criminal politicians possess various channels that equip them with the necessary skills to provide better access to public goods for their supporters. First, criminal politicians have vast access to money acquired through various illegal enterprises. On average, criminal politicians tend to be significantly richer than clean politicians.[5] They can use this cash not only to run expensive election campaigns but also to pay the financial bribes necessary to move the bureaucratic wheel. Second, criminal politicians are often construed as effective strongmen who are willing to go above the legal means to protect the right of citizens and influence the distribution of resources. They can coerce bureaucrats into diverting resources to their constituencies by using this reputation as a tactic, either by showing a willingness to 'flex their muscles' or by creating the perception that they are capable of doing so. Lastly, in developing countries, controlling resources requires strong ties with middlemen, bureaucrats, and other local leaders. Since criminal enterprises often generate employment and rent-seeking opportunities for all these state actors, fostering strong networks. Criminal politicians can activate these networks in dispensing resources to their supporters. Similar accounts can be found in the ethnographic literature on India, showing that citizens view criminal politicians as having the ability

[5] ADR (2022). "What explains the increasing entry of criminals and wealthy candidates into politics?."

to “get things done” or “Robin Hood” figures (Berenschot, 2011a, 2011b; Martin and Michelutti, 2017). Thus, if criminality serves as a positive credibility cue and criminal politicians have the necessary tools to supply benefits, voters might be rationally rewarding them, even if (but precisely because) they are criminals. Despite the availability of this rich qualitative literature, there is a lack of empirical evidence showing whether criminal politicians improve public goods provision.

In this respect, MGNREGA provides an ideal backdrop to test this hypothesis. First, empirical studies have found that welfare schemes such as MGNREGA are often used as instruments to win elections.[6] This is because MGNREGA is implemented at the village level and local politicians can often claim credit for its delivery (Gulzar and Pasquale, 2017). Second, by providing a minimum wage, the program targets the poor. There is a general agreement in the literature that clientelism is more likely to be stronger among the poorest and least educated voters (Kitschelt, 2000; Stokes et al., 2013). Since these segments of society have more immediate needs, they might be more prone to overlook probity for any short-term benefits on offer. This provides an ideal prospect for criminal politicians to target these types of voters to further strengthen clientelistic relationships, making this the best vote-buying tool at their disposal. In short, if criminal politicians are truly motivated by electoral incentives, we should expect this to be prominent when comparing criminal and clean politicians in a program of MGNREGA's importance.

To further substantiate this argument, I examine whether the program delivery varies at the constituency level. Since constituencies tend to differ in terms of electoral competition, we might expect that the incentives of criminal politicians to deliver might depend on the electoral gains on offer. To test for this, first, I examine whether the alignment of a constituency with the state government affects program delivery. The existing literature suggests that political leaders target partisan constituencies to expand their political networks and improve clientelistic relationships with their core voter base (Dasgupta, 2016; Dey and Sen, 2016). Thus, if criminal politicians aim to consolidate their chances of re-election, they should perform significantly better in such constituencies. Conversely, since these constituencies often exhibit higher rent-seeking opportunities due to better access to resources, if criminal politicians are motivated by corruption, this should be most prevalent in partisan constituencies (Arulampalam et al., 2009). Second, I explore whether there is any effect of MGNREGA's delivery depending on the constituency reser-

[6] Zimmermann (2015) find that in regions with better implementation of MGNREGA in terms of job allocation, observe a rise in voter turnout and electoral benefits for the incumbent. Dey and Sen (2016) report that the ruling state party often spent more on MGNREGA funds in their aligned constituencies. In these aligned constituencies, candidates running from the ruling party in the preceding elections often win with larger vote shares and have higher chances of being re-elected.

vation status. Seats reserved for the SC/ST category often elect candidates with a lower likelihood of being re-elected and less experience (Chattopadhyay and Duflo, 2004). Since incumbents from reserved seats are less likely to run and win, this could influence the incentives for criminal politicians to deliver the program to their constituents.[7] Lastly, I investigate whether program outcomes vary depending on whether the criminal incumbent runs for re-election. Studies have shown that electoral incentives can influence politicians' behavior to attract voters by refraining from rent-seeking and improving public goods provision (Besley, 2006; Frey, 2021). Thus, if criminal politicians are primarily driven by electoral incentives, we should expect them to maximize their position in power by performing significantly better in such constituencies.

Next, I examine whether corruption is a potential mechanism that can explain the results. First, I test whether there is any discrepancy in the average expenditure incurred across constituencies. There is sufficient evidence that officials are often complicit in reporting excess wages or overestimating expenses under the scheme (Gulzar and Pasquale, 2017; Niehaus and Sukhtankar, 2013). Thus, if criminal politicians were stealing funds from the program, we should expect to observe difference in average expenditure when comparing criminal and clean constituencies.

Second, I test whether there is any deviation between the mandated 60:40 material-labor expenditure rule between criminal and clean constituencies. MGNREGA stipulates that 60% of the expenditure must be spent on labor and the remaining 40% on materials. This law is supposed to ensure that areas do not differ in terms of the number of durable assets created and the number of work days offered under the scheme. However, due to the lack of proper monitoring, this rule is not always adhered to. Thus, if criminal politicians were engaging in corrupt practices, they should take advantage of this lack of accountability by targeting the material portion. There are several reasons for this: first, MLAs are often known to have strong ties with local contractors. Several works have found that MLAs direct projects to their preferred contractors and in exchange contractors use the profits to either fund election campaigns or provide political rents.[8] Second, the material component provides the only potential source for embezzling funds in the program. This

[7]For example, in the sample 1.14% of the SC/ST reserved incumbents recontested. Of which, 43.75% won in their respective constituencies in the subsequent election.

[8]For example, Lehne et al. (2018) using data from a rural road construction road program in India find that the share of contractors whose names match those of a winning politician increased by 83% when a new politician was elected to office. Likewise, Kapur and Vaishnav (2013) finds strong evidence of links between contractors and politicians in the cement industry, where cement consumption was highly dependent on the election cycle. Beyond India, there is a growing level of micro-evidence showing that politicians have strong links to contractors and local firms (see, Khwaja and Mian, 2005; Mironov and Zhuravskaya, 2016).

problem has been further exacerbated by the introduction of direct wage payments into the beneficiaries' bank accounts in 2008. Although in the initial years of MGNREGA, stealing from wage funds was pretty easy, the introduction of direct wage payments and other technological systems has made this nearly impossible.[9] Thus, if criminal politicians are mainly interested in amassing wealth either by rewarding contractors or stealing, we would expect them to concentrate their efforts on the material dimension of the program rather than on labor expenditure.

In contrast, if criminal politicians aim to engage in clientelism, we should expect them to concentrate their efforts on the labor component of the program. There are two main explanations for this: First, following standard models of the literature on distributive politics, criminal politicians should concentrate their efforts on distributing more jobs if electoral concerns are what drives them (Stokes et al., 2013). In fact, we should expect that voters would have little interest in the material expenditure incurred in the program. For example, Olken (2007) finds that when citizens participate in the monitoring of a road construction program in Indonesia, it led to a significant reduction in missing labor expenditure, but there was no effect on the material component. The author suggests that this can be explained as either the villagers found it easier to detect missing wages or they simply were more concerned with their private interests. Likewise, Goyal (2024) using data from India's largest rural road construction program finds that voters do not punish incumbents for poor quality or costly roads, suggesting that voters do not hold politicians responsible for corruption in the distribution of common public goods. This lack of voter accountability is especially relevant in the context of MGNREGA, which self-selects poor households. Since these households often have more immediate needs, we can easily construe that they might be more concerned with getting jobs than about the material dimension. This combined with the fact that Indian elections are fiercely competitive, makes providing access to more work opportunities a cheap vote-buying tool for politicians. Second, the expenditure rule creates a trade-off between the material and wage dimensions. Thus, MLAs must choose between engaging in corrupt practices or distributing more jobs to their citizens.

Lastly, I examine whether the findings can be explained by criminal politicians stealing from the program by over-reporting the number of beneficiaries registered in the scheme or the number of work days. MGNREGA has a history of having fake households registered in the scheme that do not officially exist ("ghost workers") or

[9] For example, Das and Maiorano (2019) conduct in-depth interviews with program implementers in West Bengal and find that it is becoming increasingly difficult and costly to steal from the labor component of the program with little electoral rewards. Likewise, Jenkins and Manor (2017) provides a list of 22 different ways to steal from the program, but shows how most of these methods have become obsolete after the introduction of direct bank payments and other e-governance systems.

a higher number of days worked reported under the scheme than actual work days ("ghost days")[10] Although I cannot directly observe the differences between the actual and reported data, I perform several robustness checks to ensure that this is not a potential channel driving the results.

# 3 MGNREGA Background

Enacted in 2005, MGNREGA was established to guarantee each rural household up to 100 days of employment in agricultural and local public work projects. Although any household can apply for the scheme, the program pays minimum wages, leading to "self-targeting" of poorer households. With a budget of about 900 billion Rupees (approximately 10 billion US$) in 2021-22, MGNREGA employs about 113 million households, making it not only the largest workforce program in India but in the world.[11] Furthermore, the program aims to improve the infrastructure of the local village (for example, irrigation of the ditches and the construction of unpaved roads) and more than 50 million local infrastructure projects have been completed under the scheme.

The implementation of MGNREGA is highly complex and the Ministry of Rural Development (MoRD) provides a detailed 232-page document with comprehensive guidelines for implementation, execution, and rights under the program.[12] I highlight a few of the key features of the program below.

The implementation of MGNREGA involves the central, state and the three levels of rural government in India known as the *Panchayat Raj*: *Zilla Parishad* at the district level, the *Panchayat Samiti* at the block level, and the *Gram Panchayat* (GP) at the village level. The program follows a bottom-up approach, where requests for work days and project approvals flow up the administrative chain, and funds flow down from the central or state government to the GPs and the beneficiaries' accounts. At the GP level, a village council meeting known as the *Gram Sabha* or *Sansad* is the primary forum for discussion of priority activities to be carried out in one year and for citizens to demand work. Based on the recommendations formulated in the *Gram Sabha* meeting, the GP prepares an annual plan and forwards it to the program officer (PO) at the block level. The PO reviews the annual plans of the individual GPs for technical feasibility and submits a consolidated statement of

[10] As mentioned earlier, the introduction of direct wage payments and other technological systems has significantly reduced corruption in labor expenditure.

[11] The data on the program is available on the national MGNREGA public data portal. Retrieved from https://mnregaweb4.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx

[12] For more details see the MGNREGA Operational Guidelines, 2013 4$^{th}$ edition. Available at https://drdashimla.nic.in/guideline/nrega.pdf

the approved proposals at the block level known as the Block Plan to the *Panchayat Samiti*. The *Panchayat Samiti* which includes the BDO and the MLA, approves the block plan and forwards it to the District Program Coordinator (DPC). The DPC then scrutinizes these proposals, consolidating them into a district plan proposal with a block-wise shelf of projects (arranged by the GPs). For each project, the district plan indicates (1) the time frame, (2) the person-days of labor to be generated, and (3) the full cost. This plan is forwarded to the *Zilla Parishad* that provides the final approval for all projects within their district. Once a project is green-lit by the district bureaucracy, the GP must execute at least 50% of the projects, as well as monitor and audit the implementation of the MGNREGA. In addition to these responsibilities, the GPs are the main body in charge of the execution of the program and are responsible for initiating and evaluating projects, registering households, issuing job cards, and allocating employment.

In terms of funding, MGNREGA is financed by the central and state government. The central government covers 75% of the material and wage expenses for semi-skilled and skilled workers and 100% of the wage costs of unskilled workers. The state government is mandated to provide the funds for the remaining expenses. Additionally, 60% of the total expenditure on projects must be spent on wages and the rest 40% on materials. Once projects are approved, funds are released from the central and state governments to the district and GPs. After due verification of the work and the muster rolls, the wages are transferred directly to the beneficiary accounts. Figure A.1 provides a detailed flow chart of the implementation and funding flow in MGNREGA.

Although the program is highly decentralized, MLAs can influence the implementation and allocation of resources at different levels of the administrative chain. First, project approvals are made at the block level, where the BDOs decide which new projects to implement and their location. The MLA has considerable power over BDOs because they can influence their employment and future transfers (Maiorano, 2014). This gives the MLA the power to intimidate BDOs to allocate projects in their preferred communities and to choose selected works that could be more visible and desirable to their voters (Aiyar and Samji, 2009; Maiorano, 2014). Second, at the village level, the GPs execute the program, with one of their main responsibilities being the allocation of jobs. The MLA can pressurize GPs to provide work selectively to their core voters. In exchange, the MLA can help GPs get projects off the ground or provide them with resources to run for re-elections (Alsop et al., 2001). In short, while the implementation of the program involves all levels of the government, MLAs have ample opportunities to divert resources to their constituents by pressuring or greasing the wheels of the bureaucratic chain.

# 4 Electoral Context

West Bengal, with a population of approximately 91 million, is the fourth most populous state in India. It is also one of the most politically significant states, with the third-largest number of seats at the national level and the second-largest number of state assembly seats. Like the rest of India, MLAs are elected for five years from a single-member constituency using the first-past-the-post voting structure, with an allowance for coalitions if a single party attains no majority.

Crime is deeply woven into the fabric of West Bengal politics. Although the rise of political candidates contesting in Indian elections is hardly a new phenomenon, the extent of the problem was not known until 2003. In a landmark judgment, the Supreme Court made it mandatory for all political candidates competing in Indian elections to submit a public affidavit. These affidavits included comprehensive details of the candidate's education, assets, liabilities, and criminal record. Remarkably, the release of these affidavits revealed that criminal candidates were regularly elected to office at both the national and state levels.

Despite the laws of the country prohibiting convicted candidates from contesting in elections, there is no such bar that forbids candidates facing trial from running. This incentivizes criminally accused candidates to compete for political office, since once in power they can potentially manipulate the judiciary to throw out the charges against them (Vaishnav, 2017). The government is cognizant of this problem and the recent uptake of criminal politicians has been frequently debated in the Indian parliament, but no serious action has been taken. Consequently, the Indian Supreme Court in 2018, instructed the parliament to make a law that at minimum prevents candidates accused of serious crimes from contesting in elections and to create special fast-track courts to expedite trials. Since all political parties are equally complicit in giving tickets to criminal candidates, little interest has been shown in passing the bill. The Supreme Court made another ruling in 2020, mandating political parties to highlight the candidates' criminal records on their social media platforms in various vernacular languages. However, this law has also had little effect in curbing the rise of criminal politicians. For example, as presented in Figure B.1, in the 2021 West Bengal state assembly elections, 49% of the 294 winning MLAs had some form of criminal charges against them, up from 38% in 2016, and 34% in 2011. Of these, 39% of the MLAs were accused of "serious" offenses (such as rape, kidnapping, and murder) in 2021, up from 32% in 2016, and 24% in 2011. The electoral success of criminal politicians is not limited to politics in West Bengal, and a similar uptake can be observed throughout the country. While these measures are a step in the right direction, the current trend suggests that there may be other mechanisms at play that might explain the rise of criminal politicians in the Indian legislature.

# 5 Data

## 5.1 Election Outcomes and Criminality Data

Data on election outcomes for the West Bengal state assembly elections for the period between 2011-2021 are collected from the Trivedi Centre for Political Data (TCPD).[13] In total, 3684 candidates contested from 572 election races in the two election cycles. The sample size is further restricted to mixed election races, where one of the top two candidates had a criminal accusation against them, providing a sample size of 249 election races. Furthermore, some of the constituents are in urban areas and do not qualify for the MGNREGA scheme.[14] Thus, these observations are dropped from the analysis, providing a final sample size of 142 election races.

The main variable of interest is the criminal accusations of the political candidates. Originally, the candidate affidavits are available on the ECI website in PDF form (Figure E.1). Association of Democratic Reform (ADR), an organization created as an election watchdog, has entered and compiled these data, making them freely available to the public.[15]

In the baseline specification, I define a criminal politician as a criminal if they are accused of any criminal charges and 0 otherwise. To further explore the robustness of the criminality variable, I examine different definitions of criminal charges. This is motivated by several reasons: First, it could be that certain candidates are "falsely" accused. This is particularly important in the Indian context since court cases can be dragged on for years, incentivizing political rivals to make false accusations to gain an electoral advantage (Prakash et al., 2019).[16] While there is no way to distinguish "false" charges from the "true" ones, I test the impact of "serious" charges on MGNREGA outcomes to alleviate this concern. Since serious charges such as rape and murder are harder to fabricate, they might be more likely

[13] TCPD has compiled the data for all the elections held both at the national and state level from the original reports available from Election Commission of India (Agarwal et al., 2021). The data is available at: https://lokdhaba.ashoka.edu.in/

[14] MGNREGA is a village-level program only applicable in rural areas. To ensure that the constituencies are similar, I consider only constituencies that have a minimum rural population of above 100,000.

[15] ADR has created a dedicated website called MyNeta, which provides data on the candidate's party affiliation, education, age, assets, liabilities, and criminal record: https://myneta.info

[16] Several studies have used the data on criminal allegations against politicians in India and have found no evidence that suggest that these allegations are false. For example, see Prakash et al. (2019) and Vaishnav (2011).

to be true. Second, it could be that the type of crime matters, and certain charges can have stronger treatment effects. For example, a politician accused of common theft might differ significantly from a politician accused of murder. For this purpose, I use the ADR definition that classifies serious crimes according to the nature of the crime and the sentencing period.[17] Next, I look at the effect of corruption charges on MGNREGA outcomes using the definition provided by Prakash et al. (2019), who consider corruption charges as ones that lead to financial loss to the government.[18]

Tables B.1 and B.2 provide the distribution of candidates by number and type of criminal charges, respectively. We can observe that the number of criminal candidates seems to be largely concentrated at the top. Of the total of candidates who contested in the elections, 17.83% of them faced some form of charges, of which 21. 61% finished in the top two positions. Likewise, of the 488 candidates accused of serious charges, 17.45% finished among the top two. Lastly, of the 216 candidates accused of corruption, 23.6% of them were able to secure the top two pole positions.

## 5.2 MGNREGA Outcomes

MGNREGA data is collected from the public data portal from 2011 to 2021. The data is available at the *Gram Panchayat* or village cluster level and include various indicators on the program such as how much work was demanded, allocation of work, the status of the projects, and the expenses incurred. I collect data on the number of projects completed, the number of days worked, the number of job cards issued, and the expenditure incurred on each component. Since the main objective of the program is to improve local infrastructure and provide rural employment, I consider two main outcomes: the number of Projects Completed and the number of Work Days. Additionally, to account for any variation in population, all outcomes are divided by per 1000 residents.

One concern with MGNREGA outcomes is that the data is available at the GP level, and mapping GPs to their respective constituencies is not straightforward. This is because in India the administrative units (such as districts,blocks) do not necessarily perfectly align with the political (constituencies) unit. To overcome this problem, data from the most recent delimitation based on the 2001 census were used to map assembly constituencies. Original delimitation orders are available on

[17]Explanation of the definition of serious crimes along with the related IPCs is available on ADR website: https://adrindia.org/content/criteria-categorization-serious-criminal-cases

[18]Prakash et al. (2019) define the following IPCs as corruption charges: 171B, 171E, 230-262, 272-276, 378-420, and 466-489D. Some examples of the charges included are bribery, counterfeiting, theft, cheating, extortion, and misappropriation.

the ECI website in PDF form. To ensure precision, I extract this data and manually map the constituencies to their respective GPs. In total, 1055 gram panchayats are mapped to the 93 unique constituencies in the sample.[19] Looking at Table B.3, we can observe that a simple comparison of MGNREGA outcomes per 1000 residents between treatment and control shows that criminal constituencies on average complete fewer projects, provide more work days, and incur a higher expenditure bill relative to clean constituencies.

# 6 Empirical Strategy

If the electoral success of criminal candidates was random, we could compare constituencies where a criminal candidate won to constituencies where a non-criminal won as a counterfactual. However, the selection of criminal candidates is highly endogenous. In other words, it could be that criminal candidates are more likely to run and win in certain constituencies than others, which would bias the estimates. To overcome this problem, I use an RD design, comparing constituencies where criminal politicians barely won to ones where they barely lost. As the margin of victory approaches zero, the success of criminal candidates in such a constituency should be as if it were random, allowing an estimation of the causal effects of electing a criminal politician (Lee and Lemieux, 2010). More formally, the empirical benchmark model that this paper estimates:

$$y_{ijt} = \alpha + \beta criminal_{jt} + \delta_1 MV_{jt} + \delta_2 criminal_{jt} \times MV_{jt} + \gamma_t + \varepsilon_{ijt} \tag{1}$$

where $y_{ijt}$ is the main outcome that measures MGNREGA outcomes in *gram panchayat i* in constituency $j$ at time $t$. $Criminal_{jt}$ is a dummy variable that equals 1 if a candidate has criminal accusations against them and 0 otherwise. The coefficient $\beta$ captures the local average treatment effect of electing a criminal politician in constituency $j$ at time $t$ on the outcome of interest. $MV_{jt}$ is the forcing variable and measures the margin of victory between criminal and clean candidates. Positive values indicate the difference between the vote share received by a criminal winner and that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner and that of a criminal runner-up. $\gamma_t$ accounts for the year fixed effects. Lastly, since the implementation of MGNREGA can vary

[19] Figure B.2 provides a constituency map of West Bengal, highlighting the treatment groups in the sample.

at both the village and the constituency level, standard errors are clustered at both levels and are denoted as $\varepsilon_{ijt}$.

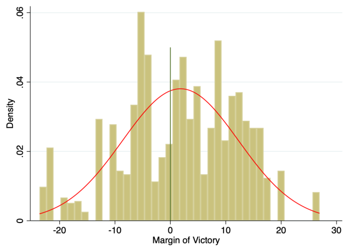
To estimate the regression, I use the bandwidth proposed by Calonico et al. (2014) or the CCT bandwidth denoted as $h$. As robustness checks, I estimate the regression using the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) or the IK bandwidth, double the optimal bandwidth ($2h$), and half the optimal bandwidth ($h/2$).

# 7 Results

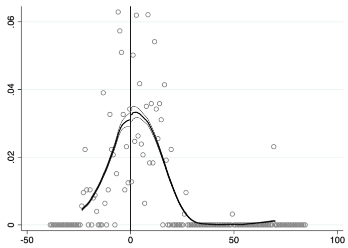
## 7.1 RDD Validity

There are two main assumptions required to validate the use of a RD design (Imbens and Lemieux, 2008). The first assumption is that there should be no manipulation of the running variable. In particular, if a criminal candidate knows that an election race is close, they may be willing to rig or manipulate the election to win. If this were the case, we would expect that there would be a larger number of criminal candidates around the threshold. A visual inspection of the density of the margin of victory provided in Figure 1 does not provide any evidence of the sorting of criminal candidates at the threshold. More formally, a McCrary (2008) density test confirms that the density of the running variable is similar below and above the cut-off.

Figure 1: Continuity of Margin of Victory between Criminal and Clean Candidates




(a) Density of Margin of Victory




(b) McCrary Density Test

**Notes:** The forcing variable is the margin of a victory that measures the difference between the vote share received by a criminal candidate and that of a clean candidate. Positive values indicate the difference between the vote share received by a criminal winner and that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner and that of a criminal runner-up. The estimated size of the discontinuity in the margin of victory (log difference in height) is 0.043 (s.e. 0.05).

The second main assumption of the RD design is that the observable characteristics that can potentially affect the outcome should be continuous throughout the threshold. Although the constituency and candidate characteristics can differ throughout the sample, they should be identical at the discontinuity.[20] Due to a lack of data availability, it is not possible to formally test every characteristic. However, a formal test for the effect of electing criminal politicians on MNREGA outcomes at time $t-1$, several constituency characteristics (such as alignment with the state ruling party, SC/ST reserved status, total votes cast in logs, voter turnout, and total electoral size in logs) and candidate characteristics (income and liabilities in logs, age, gender, possession of a high school degree, and incumbency status) provided in Table 1 show no statistical evidence of imbalances.[21] Thus, these diagnostic checks combined provide sufficient evidence for the use of an RD design.

A related concern is that the RD estimate may capture the effect of criminality and all potential compounding candidate characteristics and constituency-level characteristics that distinguish criminal and clean candidates (Marshall, 2022). To alleviate this concern, first, I estimate the RD effect by including a variety of candidate and constituency-level controls that account for any potential impact of these compounding differentials. Next, I estimate the RD effect by including candidate characteristics using the propensity score-based weighting technique. The results of these robustness checks are provided in Table C.1-C.2 shows no evidence that any other characteristic captures the effect of electing criminal politicians on the outcome of interest. However, since we cannot control for all (un) observable characteristics, I intentionally interpret the findings as the effect of electing a criminal candidate, rather than the effect of criminality alone.

[20] A description of the constituency and candidate profile for the full sample is provided in Table B.4 and Table B.5.

[21] The effect of electing criminal politicians on MNREGA outcomes at time $t-1$ is restricted to the second election cycle due to lack of data availability.

Table 1: Balance of Covariates

| Variable | Coefficient | S.E. | Obs. | Bandwidth |
|---|---|---|---|---|
| Projects Completed/1000 capita $(t-1)$ | -0.081 | 7.267 | 111 | 4.099 |
| Work Days/1000 capita $(t-1)$ | -1,566 | 1,291 | 165 | 5.497 |
| Partisan Constituency | -0.097 | 0.358 | 2459 | 4.934 |
| SC/ST Reserved Constituency | -0.256 | 0.317 | 3254 | 6.106 |
| Total Votes (in logs) | 0.0169 | 0.069 | 2107 | 4.479 |
| Voter Turnout | -0.539 | 2.515 | 2334 | 4.664 |
| Electoral Size (in logs) | 0.031 | 0.082 | 3074 | 5.863 |
| Winner Income (in logs) | -0.648 | 0.769 | 3464 | 6.766 |
| Runner-up Income (in logs) | 0.442 | 0.805 | 2724 | 5.319 |
| Winner Liabilities (in logs) | -0.168 | 3.957 | 2954 | 5.790 |
| Runner-up Liabilities (in logs) | 0.501 | 3.678 | 1982 | 4.270 |
| Winner Age | -6.673 | 5.256 | 3684 | 7.503 |
| Runner-up Age | -1.102 | 4.877 | 3719 | 7.822 |
| Winner Gender | -0.101 | 0.176 | 2954 | 5.774 |
| Runner-up Gender | -0.065 | 0.123 | 2334 | 4.665 |
| Winner High School Degree | -0.030 | 0.263 | 3464 | 6.861 |
| Runner-up High School Degree | -0.018 | 0.139 | 2394 | 4.597 |
| Winner Incumbent | -0.119 | 0.111 | 1492 | 3.334 |
| Runner-up Incumbent | 0.001 | 0.233 | 2279 | 4.597 |

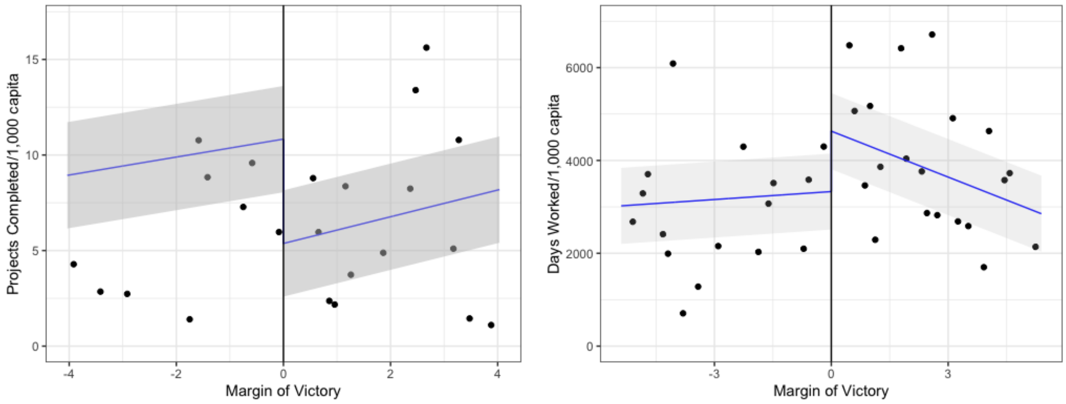
**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

## 7.2 Main Results

Figure 2 provides a graphical illustration of the main results of electing a criminal politician on MGNREGA outcomes. The plots are generated using a local linear regression with a triangular kernel and an optimal bandwidth criterion proposed by Calonico et al. (2014). A positive margin of victory indicates a constituency where a criminal candidate won against a non-criminal candidate, while a negative margin of victory implies that the criminal candidate lost and the non-criminal won. The vertical line represents the change in discontinuity when the margin is equal to zero and reflects the causal effect of electing a criminal candidate on MGNREGA outcomes.

The RD figure in panel (a) shows a clear drop at the threshold, implying that constituencies that elect a criminal politician complete fewer projects per 1000 capita relative to constituencies that elect a clean candidate. In contrast, in the RD figure in panel (b), we can observe a clear increase at the discontinuity, implying that at the threshold, constituencies that elect a criminal MLA observe a rise in work allocation per 1000 capita in comparison to constituencies that elect a clean MLA.

Figure 2: Effect of Electing Criminal Politicians on MGNREGA




(a) Projects Completed/1000 capita (b) Work Days/1000 capita

**Notes:** The forcing variable is the margin of a victory that measures the difference between the vote share received by a criminal candidate and that of a clean candidate. Positive values indicate the difference between the vote share received by a criminal winner and that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner and that of a criminal runner-up. In Figure 2(a), the y-axis represents the annual number of Projects Completed per 1000 residents. In Figure 2(b), the y-axis represents the annual number of Work Days per 1000 residents. In both figures, the x-axis represents the margin of victory. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level. The scatter plot represents the evenly spaced mimicking variance (esmv) number of bins using spacing estimators. The gray shaded area represents the 95% confidence interval. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014).

In terms of magnitude, the estimates are presented in Table 2. Column (1) reflects the estimates provided in Figure 2. In Panel A, the results are statistically significant and indicate a negative effect of electing criminal politicians on Projects Completed: On average, in constituencies where a criminal politician barely won, complete 5.26 fewer projects per 1,000 residents compared to constituencies where they barely lost. These magnitudes are substantial. To put this into context, this implies a 68% decrease in the project completion rate relative to the mean value of the dependent variable, which corresponds to a reduction of approximately 0.39 standard deviations. Also note that these estimates are yearly, meaning that during a full constituency term of five years, a criminal politician can have an extremely large impact on generating assets under the scheme. For robustness, the estimates are generated using several alternative bandwidths in columns (2)-(4). The results in column (2) with IK bandwidth are quantitatively similar to those in the main specification. Doubling the bandwidth in column (3) decreases the estimates slightly. However, halving the bandwidth in column (4) increases the magnitude.

Looking at Work Days in Panel B, the results show that constituencies where criminal MLA barely won observe a rise of 1295 Work Days per 1000 residents (implying a 36% higher work allocation relative to the mean value of the dependent variable). This corresponds to an increase in work days of about 0.33 standard deviations. Again, using various alternative bandwidths, the results remain mostly robust. In terms of magnitude, in column (2) with IK bandwidth the estimates increase slightly. In column (3) doubling the bandwidth the magnitudes reduce, but remain quantitatively and statistically significant. Finally, halving the bandwidth in column (4) the estimates lose statistical power.

Table 2: Effect of Electing Criminal Politicians on MGNREGA

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -5.264*** | -5.504*** | -3.436*** | -6.440*** |
| | (1.313) | (1.879) | (1.205) | (2.138) |
| Observations | 2459 | 1492 | 4679 | 1118 |
| Bandwidth Size | 4.916 | 3.407 | 9.832 | 2.458 |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,295*** | 1,309*** | 1,147*** | 746.2 |
| | (477.3) | (470.6) | (333.4) | (765.4) |
| Observations | 2724 | 2764 | 5044 | 1183 |
| Bandwidth Size | 5.340 | 5.458 | 10.68 | 2.670 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of Projects Completed per 1000 residents. In panel B, the outcome measures the annual number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

In the next specification, I estimate the effects of electing criminal politicians on labor expenditure per 1000 capita. The results are presented in Table 3. In column (1) the estimates show that constituencies that barely elect a criminal politician spend 193,118 Rupees (2350 US$) more per 1000 residents in comparison to constituencies that barely elect a clean politician. Again, these magnitudes are huge: this reflects a 42% increase in the wage bill relative to the mean value of the dependent variable, implying an increase of approximately 0.32 standard deviations. To provide further perspective, an average constituency comprises approximately 270,000 residents, which implies a higher wage bill of approximately 52.14 million

Rupees (626,000 US$).The average project cost ranges between 0.15 million Rupees (1,800 US$) and 0.46 million Rupees (5,600 US$). This means that if these extra funds spent on wages were allocated efficiently, they could have potentially been used to complete anywhere between 113 and 348 projects annually. The implied returns are so high that even though criminal politicians generate more employment for their constituents, they seem to reduce overall welfare significantly.

Table 3: Effect of Electing Criminal Politicians on MGNREGA Labor Expenditure

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Labor Expenditure/1000 capita | | | |
| Criminal | 193,118*** | 186,256*** | 171,649*** | 155,489 |
| | (62,455) | (70,727) | (44,093) | (103,659) |
| Observations | 2459 | 1982 | 4869 | 1118 |
| Bandwidth Size | 5.103 | 4.351 | 10.21 | 2.551 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcome measures the total labor expenditure per 1000 residents. The models include year-fixed effects and the standard errors are clustered at the gp and constituency level. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

## 7.3 Heterogeneous Effects

Until now, the estimates provided have focused on the overall cost of electing criminal politicians. However, this effect might vary at the constituency level. In particular, constituencies might differ in terms of the electoral reward on offer, which in turn could affect the delivery of the program. To test for this, in the first specification, I examine if there is any impact on the MGNREGA outcomes if the constituency belongs to the same party as that of the state ruling government. As discussed earlier, several studies highlight that politicians target partisan constituencies to improve their clientelistic relations with their core voters by providing better access to funds and work allocation under the scheme.[22] Figure 3 does not provide statistical evidence that criminal politicians running from partisan constituencies

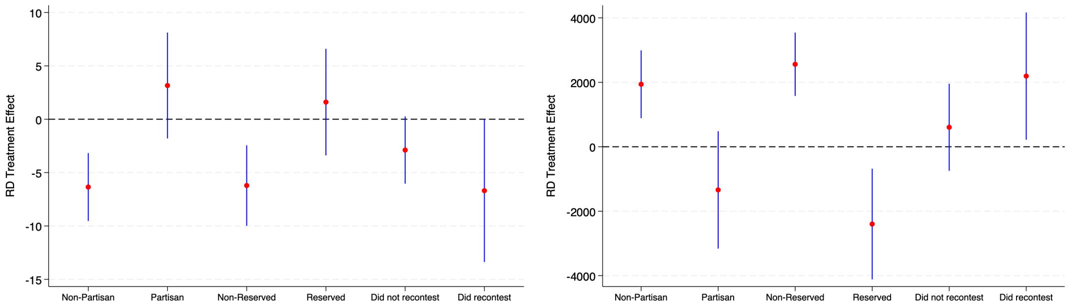
[22]For example, Das and Maiorano (2019) find that in the state of Andhra Pradesh, the state ruling party often spends more on materials in their core partisan constituencies. Likewise, Dasgupta (2016) using an RD design in the state of Rajasthan show that the allocation of labor is significantly larger in areas where the ruling party barely won versus areas in which they barely lost.

perform better. When looking at both the project completion rate and work allocation, the results suggest that there is no effect of partisanship on the program delivery.

In the next specification, I look at whether there are differences in the delivery of the program depending on the reservation status of the constituency. Generally, constituencies reserved for SC/ST candidates differ from non-reserved constituencies in several ways, such as candidate profiles, socioeconomic characteristics, and electoral rewards. Looking at Figure 3 panel (a), there is no evidence that reserved constituencies have a lower project completion rate relative to non-reserved constituencies. However, in panel (b), we can observe that the positive effect on Work Days is concentrated primarily in non-reserved constituencies. The results show that the positive effect on the allocation of work reduces by approximately 94% in reserved constituencies. This finding is consistent with the argument that criminal politicians are more likely to provide higher work allocation if there are electoral benefits on offer. "Since incumbents in reserved constituencies often face a lower probability of reelection, it makes sense that criminal politicians are less motivated to provide resources to their constituents.

In the final specification, I explore how the results change depending on whether the criminal incumbent contested the next election. Looking at Figure 3, we can see that in constituencies where the criminal incumbent seeks re-election, there is a further drop in the project completion rate. In contrast, the positive effect on work allocation is concentrated in these constituencies. This seems to suggest that criminal politicians seeking re-elections use their position of power to strategically allocate more work days to their constituencies to maximize their electoral advantage.

Figure 3: Effect of Electing Criminal Politicians by Constituency Characteristics




(a) Projects Completed/1000 capita (b) Work Days/1000 capita

**Notes:** The figure provides the treatment effect of electing a criminal politician on MGNREGA. In panel (a), the outcome measures the annual number of projects per 1000 residents. In panel (b), the outcome measures the number of Work Days per 1000 residents. Partisan indicates constituencies that are aligned with that of the state government. Reserved indicates constituencies that are reserved for the SC/ST category. Did Recontest indicate constituencies where the criminal incumbent ran for re-election in the subsequent election. All models include year-fixed effects and the standard errors are clustered at the gp and constituency level. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014).

## 7.4 Mechanisms

The results in this paper show that the election of criminal politicians has large average effects on the delivery of MGNREGA. To shed light on this phenomenon, this section examines whether these findings are the result of corruption or whether the criminal politician is using the delivery of the program to strategically provide targeted benefits to their constituents. To test this hypothesis, several measurements that could serve as indicators of corruption within the program are estimated.

As a first measurement of corruption, I look at whether there is any discrepancy in the average expenditure incurred across constituencies. In particular, I test if there are any differences in the wages paid per workday and the material expenditure per project. Since beneficiaries working under the program are paid the same minimum wage, if criminal politicians were truly generating higher employment, we should observe no discontinuity in wages paid per workday between criminal and clean constituencies. Likewise, if criminal politicians were stealing from the material component of MGNREGA, there should be visible differences in the average cost of materials when comparing criminal and clean constituencies.[23] Table 4 provides the estimates for this specification. In both Panels A-B, the estimates provide no statistical evidence of any average expenditure differentials between criminal and clean constituencies.

[23]The data only provides the reported material expenditure and there is no way of measuring discrepancies between the actual and observed expenditure. To account for this, only the material expenditure incurred for completed projects is included. Since these projects are often verified by social audit teams, the measurement error should be relatively small.

Table 4: Effect of Electing Criminal Politicians on MGNREGA Average Cost

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Wages per WorkDay | | | |
| Criminal | 0.538 | 0.675 | 3.484 | 11.10 |
| | (7.054) | (7.032) | (4.974) | (11.83) |
| Observations | 1978 | 1978 | 4171 | 878 |
| Bandwidth Size | 4.203 | 4.223 | 8.407 | 2.102 |
| | Panel B: Material Expenditure per Project | | | |
| Criminal | -18,743 | -6,442 | -1,911 | 28,749 |
| | (25,657) | (21,711) | (19,973) | (29,138) |
| Observations | 2993 | 4474 | 5211 | 1286 |
| Bandwidth Size | 6.026 | 9.873 | 12.05 | 3.013 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the wages paid per workday. In panel B, the outcome measures the material expenditure incurred on each project. The model includes year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Second, I test if there is any deviation between the mandated 60:40 material-labor expenditure rule between criminal and clean constituencies. Table 5 provides the estimates of this specification. In particular, the outcome measures the proportion of the total expenditure spent on material less than the 40% mandated requirement. In column (1) we can see that criminal politicians spend significantly less on the material component than the legal requirement. Criminal constituencies observe a drop in material expenditure by 7.20% less than the required threshold relative to clean constituencies. In columns (2)-(4) the estimates mostly remain robust and statistically meaningful across a range of alternative bandwidths. Since the MLA has to choose between distributing more jobs or spending more on materials, these findings suggest that criminal politicians seem to prefer the latter.

Table 5: Effect of Electing Criminal Politicians on MGNREGA Material Ratio

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Material Expenditure Ratio less 40% | | | |
| Criminal | -0.072*** | -0.050*** | -0.051*** | -0.047* |
| | (0.019) | (0.016) | (0.014) | (0.027) |
| Observations | 3064 | 4417 | 5343 | 1315 |
| Bandwidth Size | 6.028 | 9.753 | 12.06 | 3.014 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcomes measures the difference between the percentage of total expenditure on material less the mandated requirement of 40%. The model includes year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Next, I examine whether the higher number of work days in criminal constituencies can be explained by the existence of ghost workers or ghost days.[24] Although there is no direct method to measure the existence of ghost workers or ghost days, I conduct two main robustness checks to provide indirect evidence that this is not a potential mechanism driving the results.

First, I compare the number of job cards issued under the program between criminal and clean constituencies. Each worker must apply for a new job card when relocating to a new Gram Panchayat to indicate their willingness to work under the scheme. Table C.3 presents the estimates for this specification. The results do not suggest that the findings can be explained by a higher number of job cards issued when comparing criminal and clean constituencies. While this does not entirely eliminate the possibility of ghost workers, it does provide some reassurance that this issue is not more prevalent in criminal constituencies.

Second, I examine the robustness of the results to omitted variable bias using the method developed by Oster (2019). The model predicts how much larger the unobservables would have to be relative to the observables ($\delta$) for the treatment effect to be null ($\beta = 0$). Table C.4 presents the results for this specification.[25]

[24] A related concern is that the positive effect on the number of work days could be the result of some variation in the employment demand. Although most studies have found insignificant migration effects of MGNREGA (see, Muralidharan et al., 2016), if citizens are aware that criminal constituencies are more likely to offer better work opportunities, this could perhaps encourage them to migrate to these areas.

[25] Panel A provides the estimates for Project Completed per 1000 capita. In column (1) the estimated $\delta$ is -8.345. This implies that the unobservables to the observables need to be 8.345 times larger for the treatment effect to be zero.

Panel B column (1) shows the baseline estimates with a $\delta$ of 2.04, which means that the unobservables would need to be 2.04 times larger than the observables for the treatment effect to be zero. In columns (2)-(4), with the inclusion of various constituency and candidate controls, the coefficient remains qualitatively similar, while the R-squared and $\delta$ increase. This provides further assurance that the findings are not the result of omitted variable bias, making it less likely that ghost days can explain most of the effects.

## 7.5 Robustness

### 7.5.1 Access to Resources

In this subsection, I estimate whether there are any differences in the material expenditure incurred between criminal and clean constituencies. It could simply be that certain constituencies have better access to certain resources (i.e., materials) than others. There is enough anecdotal evidence to suggest that there could be variation in the amount of money provided for purchasing materials in certain areas or significant hold-ups in the release of funds due to bureaucratic inefficiencies. The untimely release (or lack) of funds could perhaps explain why certain areas have a higher project completion rate than others. In addition, criminal constituencies may be undertaking a larger number of capital-intensive projects. Since these projects tend to incur a higher expenditure on materials and be more time-consuming, this could perhaps explain the negative difference in the number of Projects Completed, rather than the criminal politician simply being inefficient. Table C.5 does not support this argument. If this were the case, we would observe a significantly lower allocation of the material component when comparing criminal and clean constituencies.

### 7.5.2 Alternative Definitions of Crime

In this subsection, I examine whether the delivery of MGNREGA differs depending on the type of criminal charges.[26] As mentioned earlier, there are several reasons to investigate alternative definitions of criminality, especially in the Indian context. In the first specification, I examine the effect of serious criminal charges on

[26]RD validity checks for these specifications are provided in Figure D.1 and Tables D.1-D.2. Although the treatment and control groups are mostly balanced across both constituency and candidate characteristics, in constituencies where a corrupt criminal barely won, had a lower likelihood of being SC/ST reserved and observed a lower voter turnout. In Table C.8, the estimates control for these imbalances. The results remain robust and qualitatively similar to the baseline findings. However, the coefficients increase in magnitude and suggest that corrupt politicians have higher treatment effects compared to the baseline estimates.

the main outcomes of interest. In particular, I compare constituencies where a winner has at least one serious charge (and a runner-up who has no serious charges) to constituencies where the candidate has no serious charges (and a runner-up who has at least one serious charge). The results of this exercise are presented in Table C.6. The estimates remain consistent with those of the baseline findings: constituencies that barely elect a criminal politician accused of serious charges observe a drop in the number of Projects Completed and a rise in the Work Days relative to constituencies where they barely lost. However, the magnitude of the coefficients is larger in comparison to the main results, implying that the election of serious criminals has potentially higher costs. Likewise, in Table C.7, I define a politician as a criminal if they face corruption charges against them. Again, the results are consistent and show that in constituencies where a corrupt politician barely won exhibit a drop in the project completion rate and a rise in work allocation compared to constituencies where they barely lost. Overall, these results suggest that the main findings are robust to these alternative definitions of crime, making it more likely that the criminal charges against the candidates are true.

#### 7.5.3 Timing of RD Effect

Until now, the MGNREGA outcomes included the full-time period of the MLA term between 2011 and 2020. One potential issue is that the MGNREGA data does not perfectly coincide with the election timeline. To account for this, I restrict the sample to include data only after the year the MLA was elected. In particular, for every election cycle $t$, I estimate the effect of electing criminal politicians on MGNREGA outcomes at time $t+1$. Table C.9 presents the estimates for this exercise and suggests that the results remain qualitatively similar and robust.

Another concern is that the effect of the MGNREGA outcomes might be strongest before the elections. If criminal politicians are motivated by re-election incentives, they could potentially be diverting more resources to their constituencies closer to the election cycle. To account for this, for every election held in time $t$, I drop the observations at time $t-1$. The results of this exercise are presented in Table C.10. The results remain robust with those of the baseline. However, the magnitude of both outcomes reduces slightly.

Next, I examine whether there is any variation in MGNREGA outcomes over time. Due to implementation issues, there might be a high level of annual volatility in MGNREGA. To test for this, I consider two alternative measurements: first, I estimate the effect of electing criminal politicians separately for each year of their term. Figure C.1 presents the results of this exercise with a graphical illustration of the RD effect. In panel (a), the estimates for Projects Completed show that the effect is not instantaneous and increases over time. In the first year that the criminal politician is elected, the coefficient is not statistically significant. In the second and third years, the coefficient is statistically significant and of a magnitude similar to those of the baseline. In the fourth year, the estimates increase slightly in magnitude. In the last year, the negative effect is the largest, nearly double in magnitude. In contrast, in panel (b), the positive effect on Work Days is immediate and mostly consistent in terms of magnitude across the years. Overall, these results suggest that the effect of electing criminal politicians on the MGNREGA outcomes is mostly robust throughout their term.

Lastly, to account for the year-to-year variation, I test the effect of electing criminal politicians on the MGNREGA outcomes averaged over the entire election term of five years. Table C.11 presents the results of this exercise. Looking at Projects Completed, we can observe that the estimates are statistically significant for various bandwidths, albeit the magnitude reduces slightly in comparison to the baseline. Likewise, the coefficient for Work Days is statistically significant for the main and double bandwidths. However, the coefficient loses statistical power at lower bandwidth levels.

#### 7.5.4 Addressing Extreme Values

In this subsection, I explore the robustness of the results by accounting for any outliers in the sample. In the first specification, the results are estimated by excluding very large values.[27] While these issues should not be directly correlated with the effects of electing a criminal politician, I test for this in Table C.12 by dropping the five largest values from the sample for both outcomes. Another concern is the presence of zeros in certain village clusters.[28] I address this issue in Table C.13 by dropping any observations with a 0 from the sample. In both cases, the estimates are qualitatively and quantitatively similar to the main findings. These results suggest that the findings are robust to any extreme values in the sample.

#### 7.5.5 Sensitivity of RD Specification

In this subsection, I test the robustness of the RD estimates by using different levels of bandwidth and varying the polynomial order. Figure C.2 provides estimates for both MGNREGA outcomes at different bandwidth levels. For Projects

[27] Certain regions are more densely populated or have higher state capacity which might explain the differences in MGNREGA outcomes across regions.

[28] This could be driven by several factors. First, certain projects might take longer to complete than one time period. Second, regions with scarcer inhabitants might have a lower requirement for local infrastructure or demand for work.

Completed presented in panel (a), we can observe that reducing the bandwidth though the estimates remain statically significant, the confidence interval is relatively large. Increasing the bandwidth to larger values, the estimates remain mostly stable. Likewise, the point estimates for Work Days in panel (b) are statically significant at higher bandwidths but lose statistical power at lower bandwidth levels.

Next, I estimate the treatment effects by varying the functional form. Tables C.14-C.15 report the findings of this exercise using a linear, quadratic, and cubic function with the CCT($h$), IK, $2h$, and $h/2$ bandwidths for Projects Completed and Work Days, respectively. In general, the results are consistent with those of the baseline estimates. Although using high-order polynomials or smaller bandwidths, the estimates for Work Days lose statistical power.

# 8 Conclusion

This paper attempts to find a solution to one of the most puzzling problems in politics: Why do voters support corrupt or criminal politicians? Contrary to popular belief that criminality or corruption is an undesired characteristic, my findings reveal that voters might be rationally rewarding such candidates because of their ability to provide them with targeted benefits. Despite reducing overall program efficiency, constituencies that elect criminal politicians observe a substantial rise in work allocation. The results further show that criminal politicians systematically target the wage dimension of the program, rather than materials. These findings suggest that criminal politicians compensate voters through the delivery of government schemes. Specifically, criminal politicians seem to strategically provide benefits that voters might care more about. Thus, as long as they can dispense such clientelistic goods, voters might be willing to excuse the criminal allegations against them. This is consistent with the findings of several studies that corrupt politicians engaging in pork-barrel or patronage politics can persist in democratic governments (Kitschelt, 2000; Pereira and Melo, 2015; Winters and Weitz-Shapiro, 2013). This willingness to support corrupt politicians becomes even stronger when government institutions are weak and access to resources is limited (Manzetti and Wilson, 2007). In polities of such kind, voters have no choice but to support corrupt governments for any resources they can muster.

This creates a major challenge for reformers, since the politicians in charge of strengthening state capacity and democratic functioning might have little incentive to do so. As several scholars have noted, if the politician is a criminal or corrupt, their best electoral strategy would be to pursue clientelism by engaging in parochial politics (Chandra, 2007), deepening social divisions (Vaishnav, 2017), and keeping institutions weak (Stokes, 2005). Under such conditions, voters might have an incentive to reward criminal politicians because of their ability to sell themselves as being competent and having what it takes to "get things done" in politics. Thus, curbing the demand for criminal politicians is a long-drawn process, since strengthening state capacity is slow and particularly challenging in the hands of criminal leaders.

In summary, this paper provides one of the mechanisms that could explain why voters tend to support criminal or corrupt politicians. Although this is one piece of the puzzle, the findings in this paper provide a logic for why criminal politicians not only persist but thrive in democratic countries.

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# A MGNREGA Flow Chart

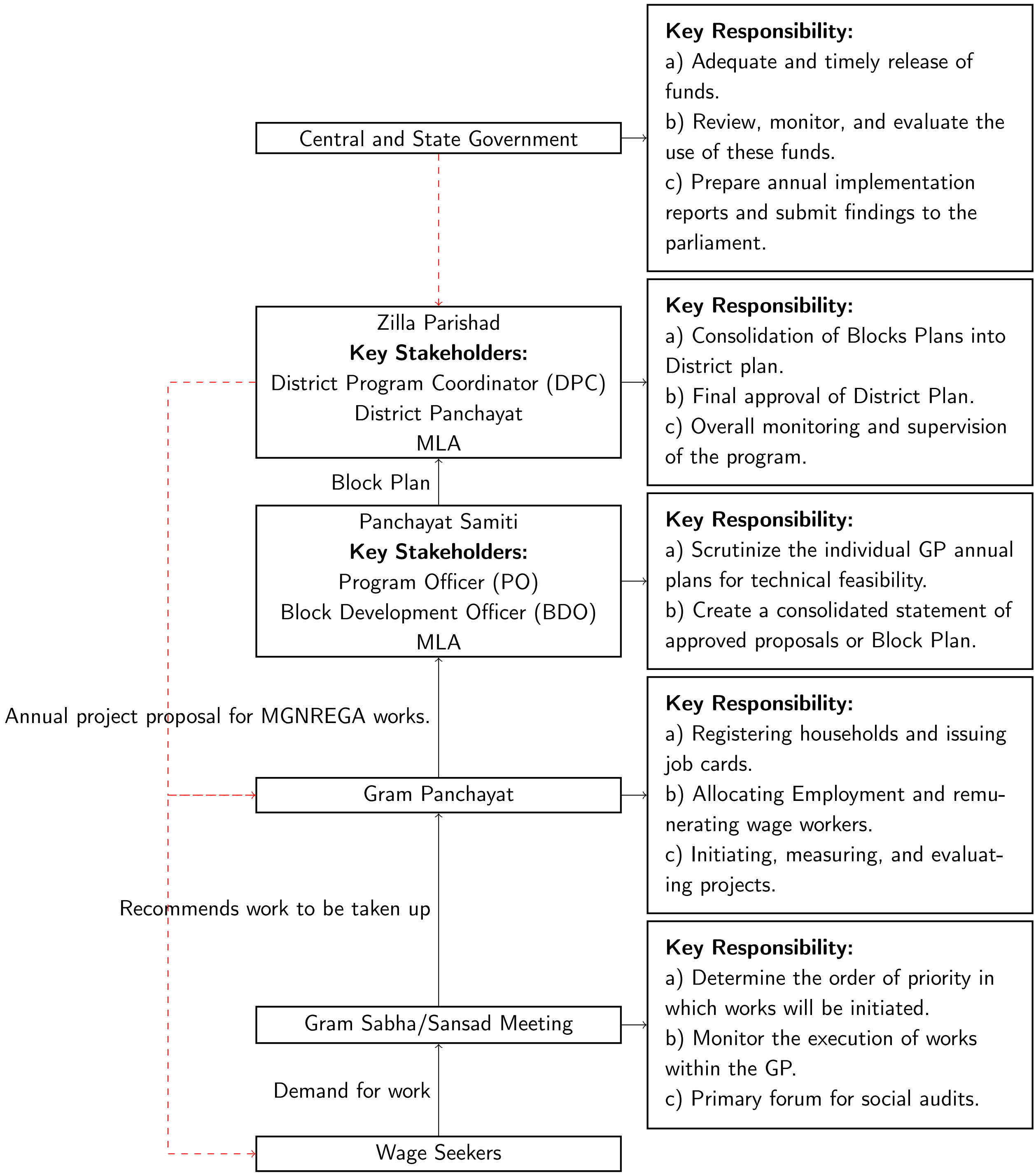
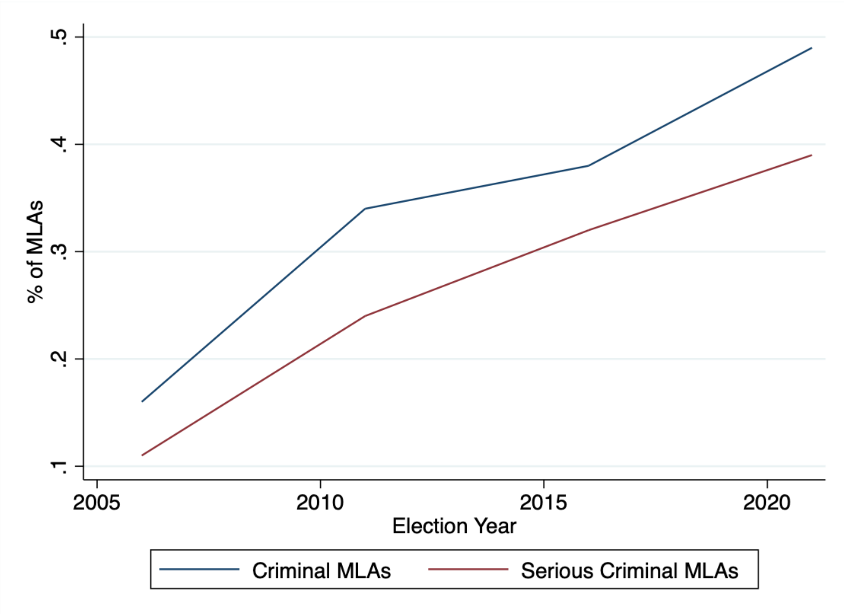



Figure A.1: MGNREGA Functioning

**Notes:** The red dashed line represents the flow of funds for MGNREGA.

## B Data and Summary Statistics

Figure B.1: % of MLAs with Criminal Records in West Bengal State Assembly Elections




**Data Source**: Association for Democratic Reform (ADR)

Table B.1: Distribution of Candidates by Number of Criminal Charges

| | Winner | Runner-up | All |
|---|---|---|---|
| 0 | 53 | 89 | 3027 |
| 1 | 28 | 29 | 334 |
| 2-4 | 40 | 20 | 224 |
| 4-6 | 11 | 0 | 33 |
| Above 6 | 10 | 4 | 46 |
| *N* | 142 | 142 | 3684 |

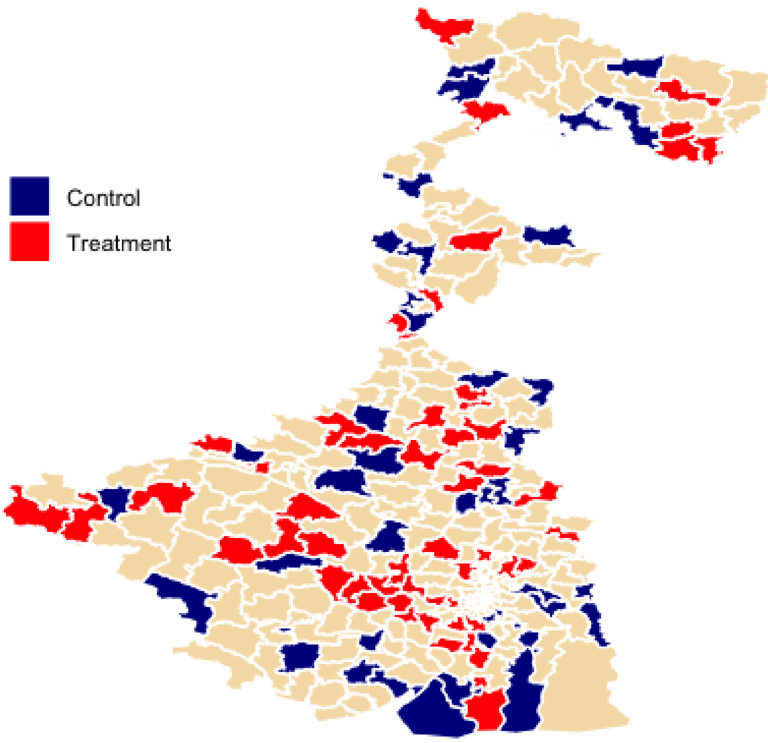
**Notes:** All refers to all the candidates that contested in West Bengal State Assembly Elections in 2011 and 2016.

Table B.2: Distribution of Candidates by Number of Criminal Charges

| | Winner | Runner-up | All |
|---|---|---|---|
| None | 53 | 89 | 3027 |
| Any Crime | 89 | 53 | 169 |
| Serious | 54 | 31 | 488 |
| Corrupt | 32 | 19 | 216 |

**Notes:** All refers to all the candidates that contested in West Bengal State Assembly Elections in 2011 and 2016.

Figure B.2: West Assembly Constituency Map by Treatment Group




**Notes**: The constituencies where a criminal politician won represent the treatment group and are marked in red. Constituencies where a criminal politician lost represent the control group and are marked in dark blue.

Table B.3: MGNREGA Outcomes per 1000 Residents

| | Control | Treatment | Average |
|---|---|---|---|
| Projects Completed | 7.897 | 7.547 | 7.690 |
| | (14.58) | (12.77) | (13.54) |
| Days Worked | 3576.10 | 3608.20 | 3595.10 |
| | (3402.10) | (4311) | (3965.70) |
| Job Cards Issued | 187.30 | 178.70 | 182.20 |
| | (112.90) | (212.10) | (178.50) |
| Labor Expenditure | 444373.70 | 467855 | 458287.80 |
| | (531105) | (654192.30) | (607135.60) |
| Material Expenditure | 144486.80 | 148488.90 | 146858.30 |
| | (311119.50) | (414672) | (375923.30) |
| Total Expenditure | 588860.60 | 616343.90 | 605146.10 |
| | (759418) | (1008164.90) | (915062.20) |

Table B.4: Constituency Profile

| Variable | Control | Treatment | Total/Average |
|---|---|---|---|
| Constituencies | 53 | 89 | 142 |
| Gram Panchayat | 650 | 940 | 1590 |
| Rural Population (in Thousands) | 315.20 | 240.80 | 271.10 |
| | (84.82) | (66.01) | (82.76) |
| SC/ST Reserved AC | 0.385 | 0.213 | 0.282 |
| | (0.487) | (0.410) | (0.450) |
| Partisan AC | 0.471 | 0.662 | 0.584 |
| | (0.499) | (0.473) | (0.493) |
| Log of Total Votes | 12.02 | 12.06 | 12.04 |
| | (0.136) | (0.111) | (0.123) |
| Voter Turnout | 87.08 | 84.31 | 85.44 |
| | (4.057) | (4.217) | (4.369) |
| Log Electoral Size | 16.49 | 16.49 | 16.49 |
| | (0.165) | (0 .131) | (0.146) |

Table B.5: Candidate Profile

| Variable | Winner | | | Runner-up | | |
|---|---|---|---|---|---|---|
| | Control | Treatment | Average | Control | Treatment | Average |
| Incumbent | 0.328 | 0.394 | 0.367 | 0.212 | 0.271 | 0.247 |
| | (0.470) | (0.489) | (0.482) | (0.409) | (0.444) | (0.431) |
| National Party | 0.905 | 0.941 | 0.926 | 0.905 | 0.941 | 0.926 |
| | (0.294) | (0.236) | (0.262) | (0.294) | (0.236) | (0.262) |
| Age | 53.62 | 53.27 | 53.41 | 50.18 | 51.40 | 50.90 |
| | (9.685) | (8.942) | (9.253) | (8.237) | (11.90) | (10.58) |
| Log Income | 14.26 | 14.90 | 14.64 | 14.21 | 14.53 | 14.40 |
| | (1.409) | (1.192) | (1.323) | (1.308) | (1.495) | (1.430) |
| Log Liabilities | 3.072 | 7.152 | 5.490 | 4.445 | 4.496 | 4.475 |
| | (5.211) | (6.428) | (6.290) | (1.308) | (1.495) | (1.430) |
| Graduate | 0.790 | 0.771 | 0.779 | 0.767 | 0.825 | 0.801 |
| | (0.407) | (0.420) | (0.415) | (0.294) | (0.236) | (0.262) |

# C Robustness Checks

Table C.1: RD Specification with Covariates

| | (1) | (2) | (3) |
|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | |
| Criminal | -3.500*** | -5.264*** | -3.500*** |
| | (1.231) | (1.313) | (1.231) |
| Observations | 4359 | 2459 | 2459 |
| Bandwidth Size | 9.020 | 4.916 | 9.020 |
| | Panel B: Work Days/1000 capita | | |
| Criminal | 1,297*** | 1,295*** | 1,297*** |
| | (430.2) | (477.3) | (430.2) |
| Observations | 3254 | 2724 | 2724 |
| Bandwidth Size | 6.235 | 5.340 | 6.235 |
| Constituency Controls | Yes | No | Yes |
| Candidate Controls | No | Yes | Yes |
| Bandwidth Type | CCT (h) | | |
| Method | Local Linear | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the measured outcome is the annual number of projects per 1000 residents. In panel B, the measured result is the annual Work Days per 1000 residents. All models include year-fixed effects and the standard errors are clustered at both the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.2: RDD with Propensity Score Matching

| | (1) | (2) |
|---|---|---|
| | Projects Completed/1000 capita | Days Worked/1000 capita |
| Criminal | -2.959** | 962.8** |
| | (1.469) | (437.7) |
| Observations | 3024 | 3109 |
| Bandwidth Size | 5.843 | 5.919 |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In column (1), the outcome measures the annual number of Projects Completed per 1000 residents. In column (2), the outcome measures the annual number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression with a triangular kernel and include weights for the candidate characteristics generated using the propensity score matching procedure. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.3: Effect of Electing Criminal Politicians on MGN-REGA Work Demand

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Job Cards Issued/1000 capita | | | |
| Criminal | -36.23 | -79.51 | -20.35 | -64.96 |
| | (32.90) | (61.65) | (20.58) | (58.27) |
| Observations | 3074 | 1118 | 5404 | 1357 |
| Bandwidth Size | 5.907 | 2.612 | 11.81 | 2.953 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcomes measures the number of job cards issued per 1000 residents. The model includes year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.4: Effect of Electing Criminal Politicians on MGNREGA:Ommited Variable Selection

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -5.264*** | -3.500*** | -3.553*** | -3.500*** |
| | (1.314) | (1.222) | (1.250) | (1.222) |
| Observations | 2,459 | 4,359 | 4,359 | 4,359 |
| R-squared | 0.175 | 0.212 | 0.204 | 0.212 |
| Delta | -8.345 | -4.489 | -4.381 | -4.489 |
| Constituency Controls | No | Yes | No | Yes |
| Candidate Controls | No | No | Yes | Yes |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,295*** | 1,297*** | 1,373*** | 1,297*** |
| | (477.5) | (455.6) | (442.7) | (455.6) |
| Observations | 2,724 | 3,254 | 3,254 | 3,254 |
| R-squared | 0.135 | 0.144 | 0.114 | 0.144 |
| Delta | 2.040 | 2.464 | 2.583 | 2.464 |
| Constituency Controls | No | Yes | No | Yes |
| Candidate Controls | No | No | Yes | Yes |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of Projects Completed per 1000 residents. In panel B, the outcome measures the annual number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). To calculate the delta, I set $R^2_{max} = 1.3R^2$ as proposed by Oster (2019). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.5: Effect of Electing Criminal Politicians on MGNREGA Material Expenditure

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Material Expenditure/1000 capita | | | |
| Criminal | -36,749 | -45,442* | -11,501 | 67,834 |
| | (30,786) | (27,121) | (29,038) | (52,357) |
| Observations | 1492 | 1982 | 3464 | 728 |
| Bandwidth Size | 3.376 | 4.230 | 6.752 | 1.688 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcome measures the total material expenditure per 1000 residents. The model includes year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.6: Effect of Electing Criminal Politicians on MGNREGA (Serious Criminals Only)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -6.208*** | -5.146*** | -4.659*** | -6.572*** |
| | (1.268) | (1.253) | (1.239) | (1.979) |
| Observations | 2017 | 2847 | 3197 | 933 |
| Bandwidth Size | 5.349 | 8.583 | 10.70 | 2.675 |
| | Panel B: Work Days/1000 capita | | | |
| Criminal | 1,634*** | 861.5 | 835.4** | 478.3 |
| | (491.7) | (668.6) | (363.4) | (731.7) |
| Observations | 2107 | 1202 | 3247 | 1107 |
| Bandwidth Size | 5.795 | 3.418 | 11.59 | 2.897 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of projects per 1000 residents. In panel B, the outcome measures the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.7: Effect of Electing Criminal Politicians on MGNREGA (Corrupt Criminals Only)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -4.333** | -9.739*** | -2.673* | -8.687*** |
| | (1.697) | (2.376) | (1.484) | (2.354) |
| Observations | 1441 | 485 | 2011 | 739 |
| Bandwidth Size | 6.236 | 2.303 | 12.47 | 3.118 |
| | Panel B: Work Days/1000 capita | | | |
| Criminal | 2,292*** | 1,240 | 1,395*** | 985.2 |
| | (664.4) | (885.4) | (509.5) | (926.2) |
| Observations | 1441 | 784 | 2071 | 739 |
| Bandwidth Size | 6.510 | 3.829 | 13.02 | 3.255 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the corrupt candidate won and 0 otherwise. In panel A, the outcome measures the annual number of projects per 1000 residents. In panel B, the outcome measures the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.8: Effect of Electing Criminal Politicians on MGNREGA with Covariates (Corrupt Criminals Only)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -6.224*** | -10.25*** | -1.710 | -8.991*** |
| | (1.831) | (2.415) | (1.584) | (2.368) |
| Observations | 1281 | 485 | 1836 | 555 |
| Bandwidth Size | 5.046 | 2.303 | 10.09 | 2.523 |
| | Panel B: Work Days/1000 capita | | | |
| Criminal | 3,338*** | 2,460*** | 2,159*** | 1,972** |
| | (646.6) | (860.3) | (506.9) | (915.0) |
| Observations | 1441 | 784 | 2071 | 739 |
| Bandwidth Size | 6.302 | 3.829 | 12.60 | 3.151 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the corrupt candidate won and 0 otherwise. In panel A, the outcome measures the annual number of projects per 1000 residents. In panel B, the outcome measures the number of Work Days per 1000 residents. Both models include year-fixed effects and controls for constituency reservation status and voter turnout. The standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.9: Effect of Electing Criminal Politicians on MGNREGA at Time t+1

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -5.985*** | -6.038*** | -4.200*** | -7.498** |
| | (2.123) | (2.236) | (1.479) | (3.753) |
| Observations | 1275 | 1183 | 2831 | 572 |
| Bandwidth Size | 3.591 | 3.407 | 7.181 | 1.795 |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,438*** | 1,417** | 1,309*** | 819.8 |
| | (549.0) | (568.8) | (380.3) | (883.6) |
| Observations | 2127 | 1947 | 3971 | 936 |
| Bandwidth Size | 5.284 | 5.006 | 10.57 | 2.642 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

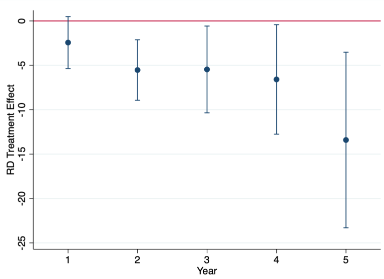
**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of projects per 1000 residents. In panel B, the outcome measures the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.10: Effect of Electing Criminal Politicians on MGNREGA Before Election Period t-1

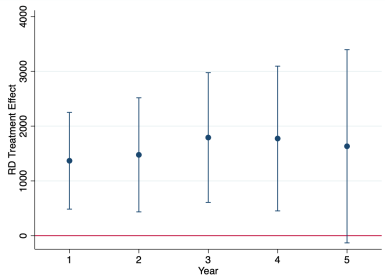
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -3.913*** | -4.023*** | -3.891*** | -4.164*** |
| | (1.285) | (1.349) | (1.040) | (1.273) |
| Observations | 3296 | 1452 | 5404 | 1588 |
| Bandwidth Size | 8.346 | 4.022 | 16.69 | 4.173 |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,234*** | 1,239*** | 1,070*** | 1,083* |
| | (413.3) | (411.2) | (290.7) | (651.7) |
| Observations | 2216 | 2216 | 4140 | 1036 |
| Bandwidth Size | 5.504 | 5.557 | 11.01 | 2.752 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of projects per 1000 residents. In panel B, the outcome measures the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.1: Effect of Electing Criminal Politicians on MGNREGA by Year




(a) Projects Completed/1000 capita




(b) Work Days/1000 capita

**Notes:** The figure provides the treatment effect of electing a criminal politician on MGNREGA each year. Year 1 indicates the year the politician was elected to office. In panel (a), the outcome measures the annual number of projects per 1000 residents. In panel (b), the result measures the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014).

Table C.11: Effect of Electing Criminal Politicians on MGNREGA for Full Election Period

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -4.835*** | -5.292*** | -2.985** | -6.372*** |
| | (1.315) | (1.964) | (1.219) | (2.121) |
| Observations | 2394 | 1357 | 4559 | 1048 |
| Bandwidth Size | 4.846 | 2.981 | 9.691 | 2.423 |
| | Panel B: Work Days/1000 capita | | | |
| Criminal | 1,434*** | 896.8 | 1,283*** | 780.4 |
| | (480.2) | (603.1) | (333.7) | (768.3) |
| Observations | 2724 | 1732 | 5044 | 1183 |
| Bandwidth Size | 5.346 | 3.994 | 10.69 | 2.673 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the average number of projects per 1000 residents. In panel B, the outcome measures the average of Work Days per 1000 residents. Both models include fixed effects for the election cycle, and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.12: Addressing Extreme Values (< Top 5 Values)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -4.929*** | -5.045** | -3.377*** | -6.766*** |
| | (1.410) | (1.971) | (1.177) | (2.291) |
| Observations | 1979 | 1289 | 4234 | 877 |
| Bandwidth Size | 4.231 | 2.848 | 8.463 | 2.116 |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,305*** | 1,263** | 1,215*** | 764.2 |
| | (486.3) | (514.9) | (336.8) | (785.0) |
| Observations | 2611 | 2391 | 4864 | 1117 |
| Bandwidth Size | 5.193 | 4.772 | 10.39 | 2.596 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

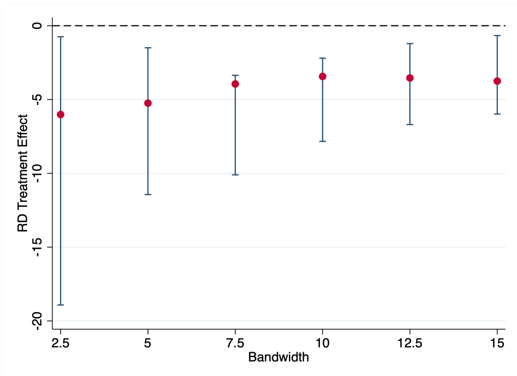
**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of Projects Completed per 1000 residents, excluding the top 5 extreme values. In panel B, the outcome measures the annual number of Work Days per 1000 residents, excluding the top 5 extreme values. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table C.13: Addressing Extreme Values (Excluding Zeros)

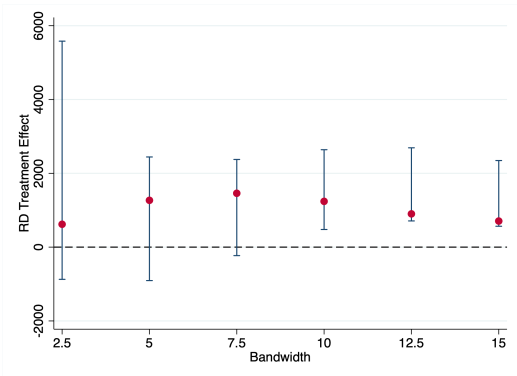
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Projects Completed/1000 capita | | | |
| Criminal | -5.101*** | -5.502*** | -3.768*** | -5.354** |
| | (1.341) | (1.970) | (1.165) | (2.125) |
| Observations | 2992 | 1513 | 5114 | 1286 |
| Bandwidth Size | 5.948 | 3.503 | 11.90 | 2.974 |
| | Panel B: Work Days /1000 capita | | | |
| Criminal | 1,374*** | 1,335*** | 1,028*** | 950.5 |
| | (486.3) | (514.9) | (336.8) | (785.0) |
| Observations | 2795 | 2554 | 5004 | 1229 |
| Bandwidth Size | 5.700 | 5.216 | 11.40 | 2.850 |
| Bandwidth Type | CCT ($h$) | IK | $2h$ | $h/2$ |
| Method | Local Linear | | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In panel A, the outcome measures the annual number of Projects Completed per 1000 residents excluding zeros. In panel B, the outcome measures the annual number of Work Days per 1000 residents excluding zeros. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure C.2: RD Estimates for Different Bandwidths




(a) Projects Completed/1000 capita




(b) Work Days/1000 capita

**Notes:** The figure provides the treatment effect of electing a criminal politician on MGNREGA for different bandwidths. In panel (a), the measured outcome is the annual number of projects per 1000 residents. In panel (b), the measured outcome is the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014).

Table C.14: RD Estimates with Different Functional Forms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Projects Completed/1000 capita | | | |
| Linear | -5.264*** | -5.504*** | -3.436*** | -6.440*** |
| | (1.313) | (1.879) | (1.205) | (2.138) |
| Quadratic | -6.494** | -7.961** | -5.153*** | -9.754** |
| | (2.555) | (3.487) | (1.439) | (4.880) |
| Cubic | -10.51** | -13.43** | -7.604*** | -6.322 |
| | (4.143) | (6.472) | (2.326) | (7.895) |
| Observations | 2459 | 1492 | 4679 | 1118 |
| Bandwidth Size | 4.916 | 3.407 | 9.832 | 2.458 |
| Bandwidth Type | | CCT (h) | | |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcome measured is the annual number of projects per 1000 residents. RD estimates are based on a local linear regression using a triangular kernel. All models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

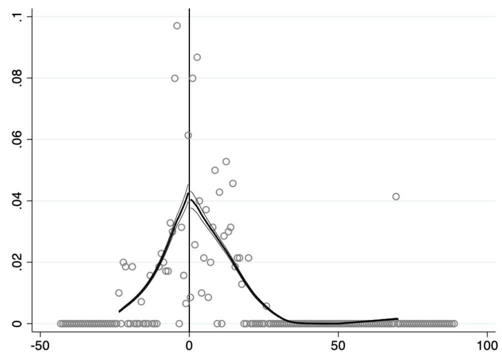
Table C.15: RD Estimates with Different Functional Forms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Projects Completed/1000 capita | | | |
| Linear | -5.264*** | -5.504*** | -3.436*** | -6.440*** |
| | (1.313) | (1.879) | (1.205) | (2.138) |
| Quadratic | -6.494** | -7.961** | -5.153*** | -9.754** |
| | (2.555) | (3.487) | (1.439) | (4.880) |
| Cubic | -10.51** | -13.43** | -7.604*** | -6.322 |
| | (4.143) | (6.472) | (2.326) | (7.895) |
| Observations | 2459 | 1492 | 4679 | 1118 |
| Bandwidth Size | 4.916 | 3.407 | 9.832 | 2.458 |
| Bandwidth Type | | CCT (h) | | |

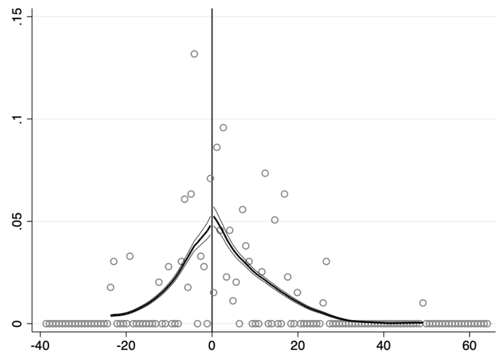
**Notes:** The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. The outcome measured is the annual number of projects per 1000 residents. RD estimates are based on a local linear regression using a triangular kernel. All models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# D RDD Validity Checks for Alternative Definitions of Crime

Figure D.1: McCrary Density Tests for Alternative Definitions of Crime




(a) Serious Criminals




(b) Corrupt Criminals

**Notes:** The forcing variable is the margin of a victory, which is the difference between the vote share received by a criminal candidate and that of a clean candidate. Positive values indicate the difference between the vote share received by a criminal winner and that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner and that of a criminal runner-up. In panel (a), a criminal equals 1 if they face serious allegations against them and 0 otherwise. In panel (b), a criminal equals 1 if they face corruption allegations against them and 0 otherwise.

Table D.1: Balance of Covariates (Serious Criminals Only)

| Variable | Coefficient | S.E. | Obs. | Bandwidth |
|---|---|---|---|---|
| Partisan Constituency | 0.083 | 0.364 | 2417 | 7.174 |
| SC/ST Reserved Constituency | -0.422 | 0.275 | 2982 | 9.743 |
| Total Votes (in Logs) | 0.017 | 0.056 | 2292 | 6.331 |
| Voter Turnout | -2.446 | 2.053 | 2212 | 6.079 |
| Electoral Size (in Logs) | -0.011 | 0.067 | 2322 | 6.393 |
| Winner Income (in logs) | -0.341 | 0.867 | 2357 | 7.138 |
| Runner-up Income (in logs) | 0.842 | 0.768 | 2982 | 9.402 |
| Winner Liabilities (in logs) | 0.893 | 3.724 | 3047 | 9.823 |
| Runner-up Liabilities (in logs) | 0.169 | 3.676 | 2357 | 6.731 |
| Winner Age | -3.665 | 4.863 | 2212 | 5.931 |
| Runner-up Age | 0.160 | 5.491 | 2357 | 6.787 |
| Winner Gender | 0.108 | 0.072 | 1622 | 4.554 |
| Runner-up Gender | -0.183 | 0.159 | 2322 | 6.409 |
| Winner High School Degree | -0.044 | 0.250 | 3719 | 7.746 |
| Runner-Up High School Degree | 0.180 | 0.141 | 2212 | 6.011 |
| Winner Incumbent | -0.041 | 0.089 | 1877 | 4.920 |
| Runner-up Incumbent | -0.015 | 0.260 | 1812 | 4.838 |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the serious criminal candidate won and 0 otherwise. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table D.2: Balance of Covariates (Corrupt Criminal Only)

| Variable | Coefficient | S.E. | Obs. | Bandwidth |
|---|---|---|---|---|
| Partisan Constituency | -0.066 | 0.347 | 1476 | 6.971 |
| SC/ST Reserved Constituency | -0.649** | 0.324 | 1781 | 8.571 |
| Total Votes (in Logs) | -0.016 | 0.072 | 1476 | 6.774 |
| Voter Turnout | -2.750* | 1.498 | 1781 | 8.795 |
| Electoral Size (in Logs) | -0.063 | 0.083 | 1441 | 6.552 |
| Winner Income (in logs) | -0.374 | 0.784 | 1781 | 8.572 |
| Runner-up Income (in logs) | 1.351 | 1.085 | 1836 | 11.160 |
| Winner Liabilities (in logs) | -0.654 | 5.882 | 1441 | 6.520 |
| Runner-up Liabilities (in logs) | -2.336 | 4.621 | 1441 | 6.231 |
| Winner Age | -8.250 | 5.350 | 1781 | 8.511 |
| Runner-up Age | 4.599 | 6.398 | 1781 | 8.888 |
| Winner Gender | 0.023 | 0.031 | 954 | 4.091 |
| Runner-up Gender | -0.290 | 0.204 | 1441 | 6.169 |
| Winner High School Degree | -0.044 | 0.250 | 3719 | 7.746 |
| Runner-Up High School Degree | 0.043 | 0.284 | 1356 | 5.989 |
| Winner Incumbent | 0.130 | 0.136 | 1721 | 8.283 |
| Runner-up Incumbent | 0.262 | 0.348 | 1321 | 5.336 |

**Notes:** The dependent variable criminal is a dummy that equals 1 if the corrupt criminal candidate won and 0 otherwise. RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). The asterisks denote the significance levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# E Candidate Affidavit

Figure E.1: Example of Candidate Affidavit

Sl.No........

भारतीय गैर न्यायिक

भारत

बीस रुपये

रु.20

Rs.20

TWENTY RUPEES

सत्यमेव जयते

INDIA

INDIA NON JUDICIAL

পশ্চিমবঙ্গ पश्चिम बंगाल WEST BENGAL 20AA 138033

AFFIDAVIT TO BE FILED BY THE CANDIDATE ALONG WITH NOMINATION PAPER BEFORETHE RUTURNING OFFICER FOR ELECTION TO LEGISLATIVE ASSEMBLY OF WEST BENGAL FROM 280,ASANSOL DAKSHIN

I, TAPAS BANERJEE Son of Late Saroj Ranjan Banerjee aged - 62 years, resident of 2 No, Mohishila Colony, PO: Asansol, PS: Asansol (south) : Dist: Burdwan, Pin-713303, a candidate at the above Election, do hereby solemnly affirm and state on oath as under :

GOVT. OF W.B. NOTARY Asansol Court W.B. Regd. No. 13/2007 ASIM BANERJEE

17 MAR 2016

(ii) **The Following cases(s) is/are pending against me in which cognizance has been taken by the court {other than the case mentioned in item (i) above }:**

| **Sl. No.** | **Offence** | **Description** |
|---|---|---|
| **(a)** | Name of the court, Case No and Date of Order taking cognizance : | Ltd ACJM : Asansol :-<br>1) Asansol (south) PS: 164/2006 (GR 840/2006)<br>2) Asansol (South) PS: 276/95<br>3) Hirapur Ps : 158/2009 dt 19/01/2009<br>4) Asansol (South) PS: GR 1599/96;321/96<br><br>Ltd SDJM Asansol: -<br>1)Asansol (south): 9/93 (GR 43/93)<br>2) Asansol GRPS :-65/90 dt 28/05/1990<br><br>Ltd. ACJM In-charge:-<br>1) NGR 816/2014 Asansol PS: GDE 1293/2014 dt 21/04/2014 under 32 Police Act. |
| **(b)** | The details of cases where the court has taken cognizance.<br>Sections of the Act and description of the offence for which cognizance taken:<br>GOVT. OF W.B. NOTARY Asansol Court W.B. Regd. No. 13/2007 ASIM BANERJEE | 1) Asansol-6RPS cases No 65/90: U/S: 147/332/427/342 IPC—9MPO Act;108IR Act<br>2) Asansol (south) PS-276/95 : U/S 148/149/323/516 IPC<br>3) Asansol(south)-164/2006; U/S 143/447/427/186/353/ GR-840/2006<br>4) Asansol (South)- 09/93;u/s147/148/149/353/323/427/435 IPCV<br>5) Hirapur PS—158/2009; u/s 143/342/352/86/353 IPC<br>6) NGR 816/2004; GDE No.- 1293/2014<br>7) Asansol (south) PS: 321/96 u/s 143/448/427/506 : 3/4 T P Act |
| **(c)** | Details of Appeal(s)/ Application (s) for revision (if any) filed against the above order(s) | **NIL** |

6) I have not been convicted of an offence(s){ other than any offence(s) referred to in sub-section (1) or sub section (2), or covered in subsection (3), of section 8 of the Representation of the People Act,1951(43 of 1951} and sentenced to imprisonment for one year or more.

If the deponent is convicted and punished as aforesaid, he shall furnish the following information ----

17 MAR 2016

**Notes**: The figure shows the first page and the relevant page with criminal charges for the winner elected from the Asansol Dakshin constituency in the West Bengal 2016 state assembly elections. The full version of the affidavit is available on the ECI website.