Manipulating the System: Clientelism and Criminality in Politics *

Abhinav Khemka†

Job Market Paper

Abstract: Why do voters often fail to reject corrupt or criminal politicians? In this paper, I argue that in settings where government institutions are weak and corruption is widespread, criminal politicians can gain control over state resources and use their delivery as a mechanism to buy voter support. To test this theory, I examine the causal effects of electing criminal politicians on India's largest rural workforce program in the state of West Bengal during the 2011 to 2020 period. Using a regression discontinuity design, I find that the election of a criminal politician leads to a drop in the number of completed projects and a rise in work allocation. This effect is more pronounced for legislators who seek re-elections, are accused of serious criminal allegations, and contest from non-reserved constituencies. The results further indicate that criminal politicians spend a significantly larger portion of the funds on the labor dimension of the program rather than on materials. These findings suggest that criminal politicians use the program to deliver clientelistic public goods to their constituents. This could explain why voters might be willing to support such candidates, despite the criminal allegations against them.

Keywords: criminal politicians, MGNREGA, elections, regression discontinuity, India.

JEL codes: D72, D73, H53,O12

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†Department of Economics, University of Barcelona and IEB, akhemka@ub.edu.

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 (Caselli & Morelli, 2004; Besley, 2006). However, citizens across 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 towards corruption or criminal candidates, but fail to punish such candidates simply because they lack the awareness to do so (Ferraz & Finan, 2008; Winters & Weitz-Shapiro, 2013). However, recent evidence has found that even when voters are presented with credible information on the candidates' criminal activities, 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 & Wilson, 2007). In other words, citizens might be making a strategic decision to support venal politicians if they are more effective at providing them with better access to public goods. This ability of criminal or corrupt politicians can be most prominent in countries that exhibit weak government institutions and the state is unable to fulfill its basic responsibilities, allowing clientelism to prosper (Easterly & Levine, 1997; Stokes, 2005). In such an environment, criminal politicians might be able to take control of state resources and use their delivery as a mechanism to buy voter support.

Despite there being some literature linking corruption or criminality to clientelism (Manzetti & Wilson, 2007; Vaishnav, 2017), the existing research has mostly found that the electoral success of low-quality legislators is often associated with harmful effects on economic development (Prakash et al., 2019), various components of the economy (Chemin, 2012; Nanda & Pareek, 2016), and a decrease in government trust (Solé-Ollé & Sorribas-Navarro, 2018). However, these studies shed little light on the impact that such politicians might have on the delivery of public goods.

In this paper, 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 targets 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 state resources in the context of India. 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 elected frequently 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 with middlemen, India is a potential scenario for clientelistic networks to thrive.

In this paper, I investigate the causal effects of electing criminal politicians on the delivery of 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 employment generation, the program aims to improve village infrastructure (e.g., roads, toilets, and canals).

I take advantage of the Indian Supreme Court judgment in 2003, mandating all political candidates contesting at both the national and state 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 criminality-accused politician on MGNREGA in the state of West Bengal during the 2011 to 2020 period. I focus on West Bengal because it is one

[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`.

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 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 a 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-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 such a constituency should be close to random (Lee & 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 fall in the number of Projects Completed by 68% and a rise 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 public goods when there are potential electoral benefits on offer.

Next, I explore if 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 sufficient evidence that corruption is a contributing factor. Instead, I find that criminal politicians spend a higher 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 en-

[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 & Papp, 2015; Muralidharan et al., 2016).

gage in rent-seeking (Olken, 2007), these results suggest that criminal politicians systematically target the wage dimension of the program as a tool to connect with their voters. Lastly, I test for various alternative explanations and conduct several robustness checks. Overall, the baseline findings remain mostly robust and consistent for a series of specifications.

This paper makes several contributions to the existing literature. Foremost, this paper contributes to the ever-growing literature trying to explain why voters elect criminal politicians in democratic countries. The existing literature provides several explanations for this surprising voter behavior, such as lack of adequate information (Ferraz & Finan, 2008), ethnic voting (Banerjee & Pande, 2007), patronage (Kitschelt & 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 be rationally rewarding such politicians because they believe this to be a necessary trait in politics.

Second, this paper contributes to the broader distributive politics literature. The findings of this paper are difficult to reconcile with the standard models of distributive politics, such as elite capture theories. For instance, Anderson et al. (2015) presents evidence from Indian villages in the state of Maharashtra, indicating that local landlord elites impede pro-poor policy implementation to keep labor compliant and wages low. In return, they secure 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 in general is negatively correlated to 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. For example Bardhan and Mookherjee (2012) theorize that politicians, especially in developing countries, often target the poor to gain voter support by delivering short-term public goods. This can give an appearance of successful implementation of pro-poor programs but often comes at the expense of providing long-term public goods such as health or education. This pattern of using clientelistic strategies can be found in several case studies, where politicians distribute targeted public resources to consolidate political power (Kitschelt & 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 on India: one that uses qualitative fieldwork argues that criminal politicians might be more adequate to "get things done" (Martin & Michelutti, 2017; Vaishnav, 2017), and the other that finds criminal politicians have adverse effects on overall economic welfare (Chemin, 2012; Prakash et al., 2019). The findings in this paper show that despite reducing 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 the theoretical discussion on why criminal politicians might be better at public goods provision. 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 RD design validity, the results, and its robustness. Section 8 provides some policy implications and concludes.

2 Theoretical Discussion

The electoral success of corruption or 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 their constituents. Under such conditions, if criminal politicians are more effective at providing specific public goods, citizens might be willing 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.

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. For example, 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 fulfill the basic needs of citizens (Stokes, 2005; Manzetti & Wilson, 2007). 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 in pay 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 control over resources requires strong ties with middlemen, bureaucrats, and other local leaders. In this respect, criminal en-

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

terprises often generate employment and rent-seeking opportunities for all these state actors fostering strong networks. In turn, criminal politicians can activate these networks in dispensing resources to their supporters. Similar accounts can be found in the ethnographic literature across India, showing that citizens view criminal politicians as having the ability to “get things done” or “Robin Hood” figures (Berenschot, 2011a, 2011b; Martin & Michelutti, 2017). Thus, if criminality serves as a positive credibility cue and criminal politicians have the necessary tools to supply public good, voters might be rationally rewarding such politicians, even if (but precisely because) they are criminals. Despite the availability of this rich ethnographic literature, there is a lack of empirical evidence showing if criminal politicians are better at 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 & 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 the probity of the short-term benefits on offer. This provides an ideal prospect for criminal politicians to target these types of voters to further strengthen clientelistic relationships. Lastly, the money available under the MGNREGA is considerable, often exceeding the discretionary funds of the MLA, making this the best vote-buying tool at their disposal.[7] In short, if criminal politicians are truly motivated by electoral incen-

[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.

[7]Each MLA in West Bengal has an annual budget of 60 lakh Rupees (70,000 US$ approximately) to spend at their discretion for local area development (MLAADS). In comparison, in the average sample constituency, the annual total expenditure incurred on the program was about 14.1 crore Rupees (approximately 1.6 million US$ approximately), out of which about 76% was spent on wages.

tives, 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 public goods to their citizens 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. Existing literature suggests that political leaders may target partisan constituencies to expand their political networks and enhance clientelistic relationships with their core voter base (Dey & Sen, 2016; Dasgupta, 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 reservation status. Seats reserved for the SC/ST category often elect candidates with a lower likelihood of being re-elected (Bhavnani, 2017) and less experience (Chattopadhyay & Duflo, 2004). Since reserved seats offer a lower probability of re-election, this factor might influence the incentives for criminal politicians to deliver the program to their constituents. 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.

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.

While 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.[8] In addition, the program aims to improve local village infrastructure (for example, ditch irrigation and unpaved road building) and over 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.[9] I highlight a few of the key features of the program below.

The implementation of MGNREGA involves the central, state, and all three tiers 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 on priority activities to be taken up in a 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 scrutinizes the annual plans of the individual GPs for technical feasibility and submits a consolidated statement of approved proposals at the block level known as the Block Plan to the *Panchayat Samiti*. The *Panchayat Samiti* which includes the BDO and MLA discusses and 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 GPs). For each project, the district plan indicates (1) the time frame, (2) the person-days

[8]The data on the program is available on the national MGNREGA public data portal. Retrieved from `https://MGNREGAweb4.nic.in`

[9]For more details see the MGNREGA Operational Guidelines, 2013 4th edition. Available at `https://nrega.nic.in/Circular_Archive/archive/Operational_guidelines_4thEdition_eng_2013.pdf`.

of labor to be generated, and (3) the full cost. This plan is forwarded to the *Zilla Parishad* which discusses and provides final approval for all the 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, GPs are the main body in charge of the execution of the program and responsible for initiating and evaluating projects, registering households, issuing job cards, and allocating employment.

In terms of funding, MGNREGA is financed by both the central and state governments. 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 the 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 directly transferred into the beneficiary accounts. Figure A.1 provides a detailed flow chart of the implementation and funds flow in MGNREGA.

Despite the program being highly decentralized, MLAs can influence the implementation and allocation of resources at different levels of the administrative chain. First, the project approvals are made at the block level, where BDOs decide what 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 intimate BDOs to allocate projects in their preferred communities (Maiorano, 2014) and to choose selected works that might be more visible and desirable to their voters (Aiyar & Samji, 2009). Second, at the village level, 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 to get projects off the grounds or provide them with resources to run for re-elections (Alsop et al., 2001). In short, while the implementation of the program involves all the tiers 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 very much intertwined 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 compulsory for all political candidates contesting 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 both at the national and state levels.

Although the laws of the country prohibit convicted candidates from contesting in elections, there is no such bar forbidding 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 in throwing 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 actions have been taken. Consequently, the Indian Supreme Court in 2018, instructed the parliament to make a law that at the 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, there has been little interest 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 also has had little effect in curbing the rise of criminal politicians. For example, as presented in Figure B.1, in the West Bengal state assembly elections of 2021, 49% of the 294 winning MLAs had some form of criminal charges against them, up from 38% in 2016, and 34% in 2011. Out of which, 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. This electoral success of criminal politicians is not limited to West Bengal politics, and a similar uptake can be observed all across the country. While these measures are a step in the right direction, the current trend suggests that there might 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 is collected from the Trivedi Centre for Political Data (TCPD).[10] In total, 3684 candidates contested from 572 election races across 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. Additionally, certain of the constituencies lie in urban areas and do not qualify for the MGNREGA scheme.[11] 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. Association of Democratic Reform (ADR), an organization created as an election watchdog has re-entered and compiled this data making it freely available to the public on their social media platform to provide better access and

[10]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/`.

[11]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.

improve political accountability.[12] Using this data, in the baseline specification, I define a binary variable that equals 1 if the politician is 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).[13] Although there is no way of distinguishing the "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 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 significantly differ from a politician accused of murder. For this purpose, I use the definition provided by ADR that classifies serious crimes according to nature of crime and sentencing period.[14] 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 the ones that lead to a financial loss to the government.[15]

Table B.1 and Table 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 candidates

[12]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`.

[13]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 Vaishnav (2011); Prakash et al. (2019).

[14]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`.

[15]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. For further details on related IPCs see: `https://adrindia.org/content/criteria-categorization-serious-criminal-cases`.

that contested in the elections, 17.83% of them faced some form of charges, out of which 21.61% of them finished in the top two positions. Likewise, from the 488 candidates accused of serious charges, 17.45% finished amongst the top two. Lastly, out of 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 includes various indicators on the program such as how much work was demanded, allocation of work, status of projects, and the expenditure 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 constituencies 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. Past studies have used polygon shape files to map constituencies to their respective villages (Asher et al., 2021). One challenge with this procedure is that the same village might overlap over two constituencies. To overcome this problem, I use data from the most recent delimitation based on the 2001 census to map assembly constituencies. The original delimitation orders are available on 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.[16] Looking at Table B.3, we can observe that a simple comparison of MGNREGA outcomes per 1000 residents

[16]Figure B.3 provides an assembly constituency map of West Bengal, highlighting the treatment groups in the sample.

between the 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 from certain constituencies over others, which would bias the estimates. To overcome this problem, I use a 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 constituency should be as if it is random, allowing an estimation of the causal effects of electing a criminal politician (Lee & Lemieux, 2010). More formally, the benchmark empirical model this paper estimates:

$$y_{ijt} = \alpha + \beta criminal_{jt} + \delta_1 MV_{jt} + \delta_2 criminal_{jt} \times MV_{jt} + \gamma_t + \epsilon_{ijt} \qquad (1)$$

where y_{ijt} is the main outcome measuring the 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 β 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 the criminal and clean candidates. Positive values indicate the difference between the vote share received by a criminal winner less that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less that of a criminal runner-up. γ_t accounts for the year fixed effects. Lastly, since the implementation of MGNREGA can vary both at the village and constituency level, the standard

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

errors are clustered at both levels and denoted as ϵ_{ijt}.

To estimate the regression, I use the bandwidth proposed by Calonico et al. (2014) or CCT bandwidth denoted as h. As robustness checks, I also estimate the regression using the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) or 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 & Lemieux, 2008). The first assumption is that there should be no manipulation of the running variable. In particular, if a criminal candidate knows an election race is close, they may be willing to rig or manipulate the election to win. If this was 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(a) does not provide any evidence of sorting of criminal candidates at the threshold. More formally, a McCrary (2008) density test provided in Figure 1(b) confirms the density of the running variable is similar below and above the cut-off.

The second main assumption of the RD design is that the observable characteristics that can potentially affect the outcome should be continuous across the threshold. Although the constituency and candidate characteristics can differ over the entire sample, they should be identical at the discontinuity.[17] Due to a lack of data availability, it is not possible to formally test every characteristic. However, a formal test for 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) that can potentially affect the outcome or be related to criminality is provided in Table 1-2. The estimates provide no statistical evidence of imbalances. Thus, these diagnostic checks put together provide sufficient evidence for the use of a RD design.

A related concern is that the RD estimate may capture the effect of criminality and all potential compounding candidate and constituency-level characteristics that distinguish criminal and clean candidates (Marshall, 2022). To address this, I perform a battery of robustness checks including a variety of candidate and constituency level control accounting for any potential effect of these compounding differentials.[18] Thus, this provides some assurance that the findings in this paper capture the effect of electing criminal politicians on the outcome of interest rather than any other potentially correlated compounding factors.

Table 1: Balance of Constituency Characteristics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Partisan	SC/ST Reserved	Log Total Votes	Voter Turnout	Log Electoral Size
Criminal	-0.097	-0.256	0.0169	-0.539	0.031
	(0.358)	(0.317)	(0.069)	(2.515)	(0.082)
Observations	2459	3254	2107	2334	3074
Bandwidth Size	4.934	6.106	4.479	4.664	5.863
Method	Local Linear				

Notes: The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[17] A description of the constituency and candidate profile for the full sample is provided in Table B.3 and Table B.4.

[18] The results of this exercise are provided in Table C.10 and remain qualitatively similar to the main findings.

Table 2: Balance of Candidate Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Log Income	Log Liabilities	Age	Gender	High School Degree	Incumbent	National Party
				Panel A: Winner			
Criminal	-0.648	-0.168	-6.673	-0.101	-0.030	-0.119	0.095
	(0.769)	(3.957)	(5.256)	(0.176)	(0.263)	(0.111)	(0.120)
Observations	3464	2954	3684	2954	3464	1492	3784
Bandwidth Size	6.766	5.790	7.503	5.774	6.861	3.334	8.001
				Panel B: Runner-up			
Criminal	0.442	0.501	-1.102	-0.065	-0.018	0.001	0.095
	(0.805)	(3.678)	(4.877)	(0.123)	(0.139)	(0.233)	(0.120)
Observations	2724	1982	3719	2334	2394	2279	3784
Bandwidth Size	5.319	4.270	7.822	4.665	4.801	4.597	8.001
Method				Local Linear			

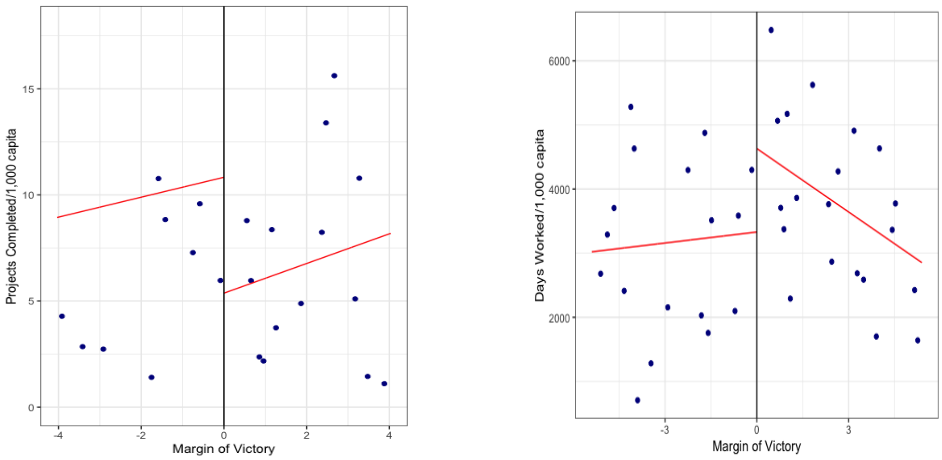
Notes: The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth uses a mean-squared error optimal bandwidth selector proposed by Calonico et al. (2014). Asterisks denotes 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 Figure 2(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 Figure 2(b) we can observe a clear rise 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 from that of a clean candidate. Positive values indicate the difference between the vote share received by a criminal winner less that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less 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 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 3. Column (1) reflects the estimates provided in Figure 2. The estimates are generated using the optimal bandwidth (h) criterion proposed by Calonico et al. (2014). 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 1000 residents in comparison to constituencies where they barely lost. These magnitudes are substantial. To put this in context, this implies a 68% decline in project completion rate relative to the mean value of the dependent variable, which corresponds to a reduction by about 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, I generate the estimates using several alternative bandwidths in columns (2)-(4). In column (2) I use the IK bandwidth and in columns (3)-(4) I use double and half the CCT bandwidth, respectively. 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. While halving the bandwidth in column (4) increases the magnitude.

When 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 a rise in Work Days by 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 3: 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 measured is the annual number of Projects Completed per 1000 residents. In Panel B, the outcome measured is 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. The 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). Asterisks denotes 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 4. In column (1) the estimates show that constituencies that barely elect a criminal politician spend 193,118 Rupees (2350 US$) more per 1000 residents in comparison to constituencies that barely elect a clean politician. Again, these magnitudes are huge: this reflects a 42% rise in the wage bill relative to the mean value of the dependent variable, implying an increase by about 0.32 standard deviations. To provide further perspective, an average constituency comprises about 270,000 residents, implying a higher wage bill of approximately 52.14 million Rupees (626,000 US$). On average, the 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 4: 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 measured is 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. The 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). Asterisks denotes 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.[19] Figure 3 provides no statistical evidence that criminal politicians running from partisan constituencies 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.

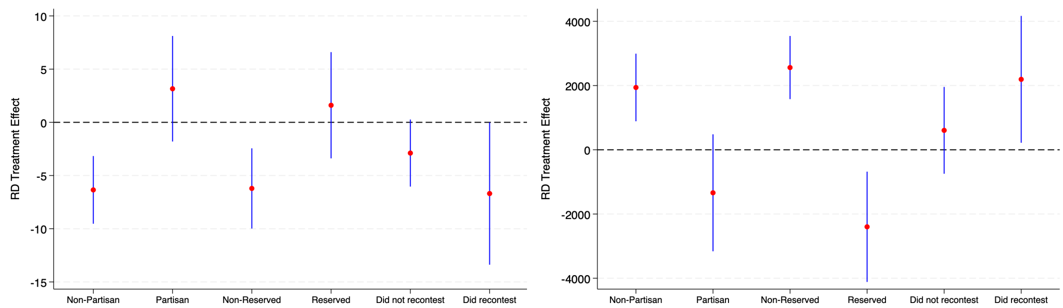
In the next specification, I look at if there are any differences in the delivery of the program depending on the reservation status of the constituency. Generally, constituencies reserved for SC/ST candidates differ from non-reserved constituencies in several ways, such as candidate profiles, socio-economic 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 in work allocation reduces by about 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 in reserved constituencies, the incumbent often observes a lower probability of re-election (Afridi et al., 2017; Bhavnani, 2017), it makes sense that the elected politician is less motivated to provide resources to their constituents.

In the last specification, I examine if the results vary depending on whether the criminal incumbent ran in the next election cycle. Looking at Figure 3, we can see that the results indicate 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 result seems to suggest that criminal politicians seeking re-elections use their po-

[19]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 a 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.

sition 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 measured is the annual number of projects per 1000 residents. In Panel (b), the outcome measured is 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. The 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 two potential underlying mechanisms that may account for these results. Specifically, I investigate whether these findings are a result of rent-seeking activities or whether the criminal politician is using the delivery of the program to strategically provide targeted benefits to their constituents. To test this hypothesis, I estimate several measurements that could serve as indicators of corruption within the program.

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. There is sufficient evidence that officials are often complicit in reporting excess wages or overestimating expenses under the scheme (Niehaus & Sukhtankar, 2013; Gulzar & Pasquale, 2017). 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 material cost when comparing criminal and clean constituencies.[20] Table 5 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.

Table 5: 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 measured is the wages paid per workday. In Panel B, the outcome measured is 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. The 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). Asterisks denotes the significance levels: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Next, I test if there is any deviation between the mandated 60:40 material-labor expenditure rule between criminal and clean constituencies. As discussed earlier, MGNREGA stipulates that 60% of 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

[20]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, I only include material expenditure incurred for completed projects. Since these projects are often verified by the social audit teams, the measurement error should be relatively small.

offered under the scheme. However, due to a lack of proper monitoring, this rule is not always adhered to. Thus, if criminal politicians were partaking in corrupt practices, they should take advantage of this lack of accountability by targeting the material portion of the program. 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.[21] Second, the material component provides the only potential source for embezzling funds in the program. For example, Afridi and Iversen (2013) using social audit reports, find substantial irregularities in the material expenditure of the program.[22] This problem has been further exacerbated by the introduction of direct wage payments into the beneficiaries' bank accounts in 2008. Although the initial years of MGNREGA did have discrepancies in wage payments, now what has remained to siphon money from is only the material component (Jenkins & Manor, 2017). In short, 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. Table 6 provides the estimates of this specification. In particular, the outcome measured is 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

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

[22]There is substantial literature that has used social audits reports to examine leakages between the actual expenditure incurred and the reported expenditure not only in MGNREGA but in similar large-scale development programs across the world (for e.g., Olken, 2007; Banerjee et al., 2020). These studies have found consistent hard evidence that the discrepancies seem to be always higher in materials than in other channels.

bandwidths.

Table 6: 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 measured are the difference between the percentage of total expenditure spent 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These findings seem to indicate that criminal politicians are strategically providing targeted benefits to their constituents, rather than engaging in corrupt practices. There are two main explanations for this: First, following standard models of distributive politics literature, 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) using a field experiment in Indonesia finds that when villagers were informed about corruption in a road construction program, it led to a sizeable 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. This 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 about getting jobs than 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 material and wage dimensions. This means that MLA has to choose between distributing more jobs or spending more on materials. The findings in this paper indicate that criminal politicians seem to prefer the latter.

7.5 Alternative Explanations

In the preceding sections, the results seem to indicate that although the election of a criminal politician leads to negative effects on local infrastructure growth, they are substantially better at providing work opportunities to their constituents. Two plausible alternative explanations could partly be driving these results. In particular, constituencies could differ in terms of fund allocation or employment demand which could be contributing to the baseline findings.

To test for this, in the first specification, I estimate if 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. Moreover, 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.1 provides no support for this argument. If this were the case, we would observe a significantly lower allocation of the material component when comparing criminal and clean constituencies.

A second explanation contributing to the positive effect in the number of Work Days could be a result of some variation in the employment demand. Although rural-rural migration is rare, if citizens are aware that in constituencies where a criminal politician won are more likely to offer better work opportunities, this could perhaps encourage them to migrate to these areas. Another related concern is that the program suffers from having fake households registered under the scheme that do not officially exist.[23] These factors could potentially explain the differences in work allocation when comparing criminal and clean constituencies.

[23] Although the initial years of the program suffered from fake job cards being issued, this problem has considerably reduced by the introduction of e-governance systems in 2011 (Banerjee et al., 2020).

One way to test for this is to look at the number of job cards issued under the program.[24] Each worker indicating their willingness to be employed under the scheme needs to apply for a new job card when moving to a new *Gram Panchayat*. Table C.2 provides the estimates for this result and provides no statistical evidence that there are any differences in the number of job cards issued when comparing criminal and clean constituencies. These results seem to suggest that the employment demand was relatively similar across the treatment and control groups. Overall, this put together with the findings in Table C.1 provides some assurance that the results do not seem to be driven by differences in material expenditure or employment demand.

7.6 Robustness

7.6.1 Alternative Definitions of Crime

In this subsection, I examine if the delivery of MGNREGA differs depending on the type of criminal charges.[25] 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 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 clean candidate has no charges (and a runner-up who has at least one serious charge). The results of this exercise are presented in Table C.3. 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

[24] Ideally, I would like to precisely test if there is any rural migration effect, but due to data constraints, the number of job cards is the best alternative measurement available. Additionally, several studies have generally found insignificant migration effects of MGNREGA (see, Muralidharan et al., 2016).

[25] RD validity checks for these specifications are provided in Figure D.1 and Tables D.1-D.4. 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.5, 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 in comparison to the baseline estimates.

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.4, 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 in comparison to constituencies where they barely lost. Overall, these results put together suggest that the main findings are robust to these alternative definitions of crime, making it more likely that criminal charges against the candidates are true.

7.6.2 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 data on MGNREGA does not perfectly coincide with the timeline of the elections. 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.6 presents the estimates of this exercise and suggests that the results remain qualitatively similar and robust.

Another concern is that the effect of the MGNREGA outcomes might be at its strongest before elections are held. 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.7. The results remain robust with those of the baseline, however, the magnitude for both outcomes reduces slightly.

Next, I examine if 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 of the criminal politician being elected, the coefficient is not statistically significant. In the second and third years, the coefficient is statistically significant and of a similar magnitude to those of the baseline. In the fourth year, the estimates increase slightly in magnitude. In the last year, the negative effect is at the largest, nearly doubling 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 MGNREGA outcomes is mostly robust over their whole 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.8 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 the bandwidth. However, the coefficient loses statistical power at lower bandwidth levels.

7.6.3 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, I estimate the results by excluding very large values.[26] While these issues should not be directly correlated with the effects of electing a criminal politician, I test for this in Table C.9 by dropping the five largest values from the sample for both outcomes. Another concern is the presence of zeros in certain village clusters.[27] I address this issue in Table C.10 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.

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

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

7.6.4 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 the estimates for both MGNREGA outcomes at different bandwidth levels. For Projects Completed presented in panel (a), we can observe that reducing the bandwidth though the estimates remain statically significant, the confidence interval is relatively large. While 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.

In the next specification, I estimate the treatment effects by varying the functional form. Table C.11-C.12 reports 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. Overall, the results look consistent with those of the baseline estimates. Although at high-order polynomials or smaller bandwidths, the estimates for Work Days lose statistical power.

The last robustness check, I conduct is adding various covariates in the model. The results of this exercise are presented in Table C.12. In column (1) the estimates include constituency controls for whether the constituency was reserved for SC/ST, the winner was aligned with the ruling state government, the number of voters, and the voter turnout. In column (2) the estimates reported include candidate controls for their gender, age, income, liabilities, incumbency, and whether the candidate belonged to the ruling state government party for both the winner and the runner-up. In column (3) the results reported include both the constituency and candidate level controls. Overall, the results remain statistically significant and close to those of the main findings. This suggests that the estimates are a result of the effects of electing criminal politicians rather than some other correlated candidate or constituency characteristic.

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 distribute public goods. 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 public goods. Specifically, criminal politicians seem to strategically deliver specific public goods 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 who engage in pork-barrel or patronage politics can persist in democratic governments (Kitschelt, 2000; Winters & Weitz-Shapiro, 2013; Pereira & Melo, 2015). This willingness to support corrupt politicians becomes even stronger when government institutions are weak and access to resources is limited (Manzetti & 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.

To summarize, 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 research provide a logic for why criminal politicians not only persist but thrive in democratic countries.

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9 Appendix

A. MGNREGA Flow Chart

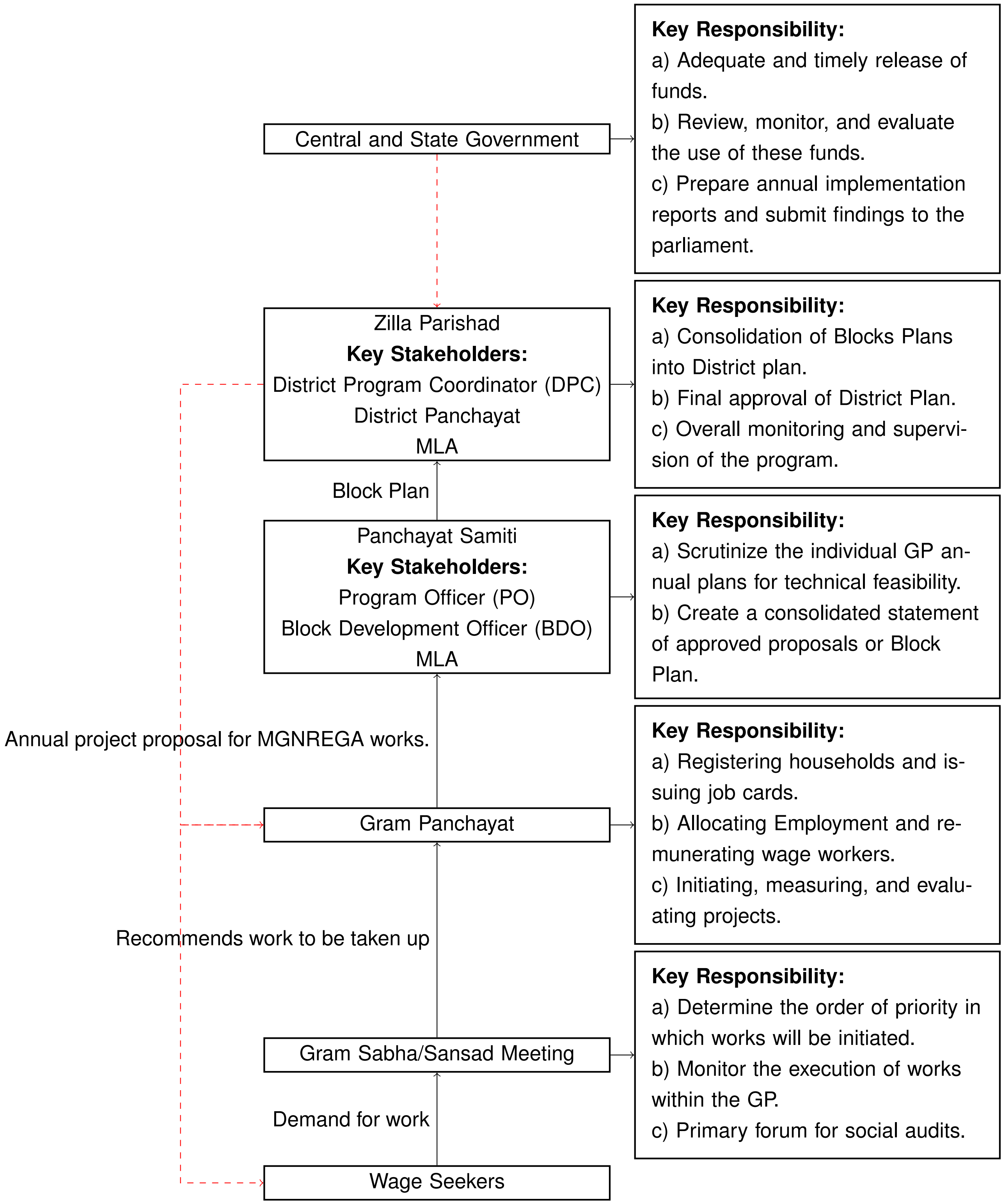
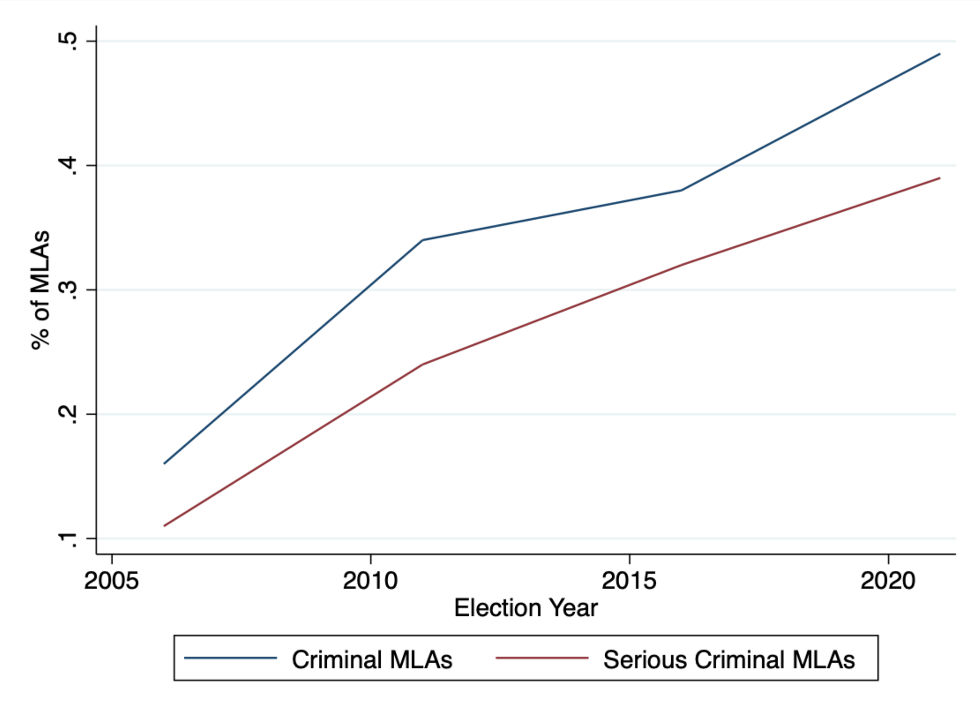


Figure A.1: MGNREGA Functioning:

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

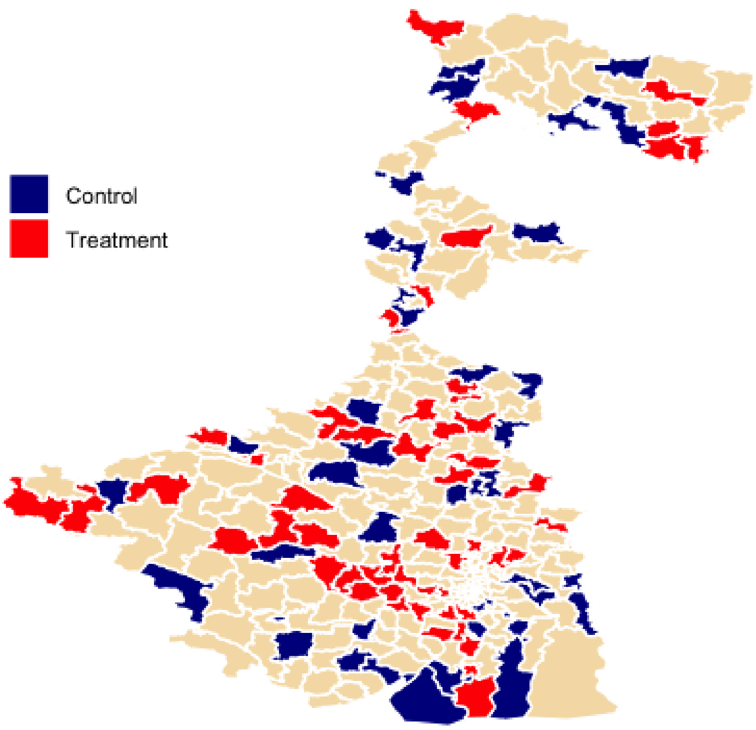
Notes: All refers to all the candidates that contested in West Bengal State Assembly Elections in 2011 and 2016.

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: 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 measured is 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Effect of Electing Criminal Politicians on MGNREGA 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 measured is 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: 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 measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured 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 and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: 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 measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured 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 and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: 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 measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured is the number of Work Days per 1000 residents. Both models include year-fixed effects and controls for the constituency reservation status and voter turnout. The standard errors are clustered at the gp and constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: 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			

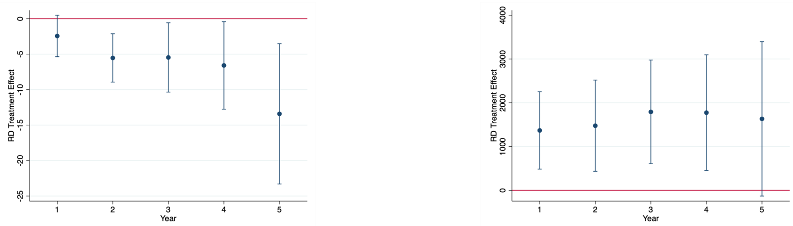
Notes: The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In Panel A, the outcome measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured is the number of Work Days per 1000 residents. Both models include year-fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: 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 measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured 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 and given in parentheses. The 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). Asterisks denotes 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 measured is the annual number of projects per 1000 residents. In Panel (b), the outcome measured 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. The 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.8: 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 measured is the average number of projects per 1000 residents. In Panel B the outcome measured is 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.9: 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			

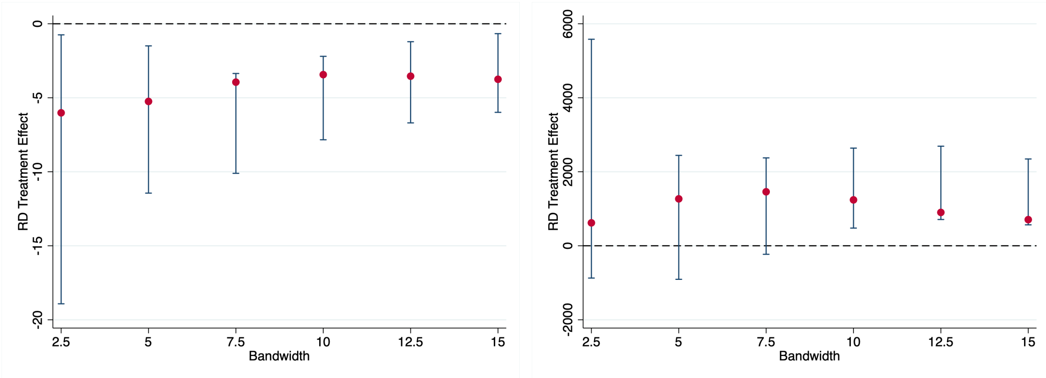
Notes: The dependent variable criminal is a dummy that equals 1 if the criminal candidate won and 0 otherwise. In Panel A, the outcome measured is the annual number of Projects Completed per 1000 residents, excluding the top 5 extreme values. In Panel B, the outcome measured is the annual number of Work 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.10: 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 measured is the annual number of Projects Completed per 1000 residents excluding zeros. In Panel B, the outcome measured is 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. The 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). Asterisks denotes 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 outcome measured is the annual number of projects per 1000 residents. In panel (b), the outcome measured 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. The 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: 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.12: RD Estimates with Different Functional Forms

	(1)	(2)	(3)	(4)
	Work Days /1000 capita			
Linear	1,295***	1,309***	1,147***	746.2
	(477.3)	(470.6)	(333.4)	(765.4)
Quadratic	837.1	828.8	1,644***	2,134
	(814.0)	(800.8)	(538.2)	(1,608)
Cubic	1,503	1,448	898.1	11,150***
	(1,419)	(1,354)	(750.9)	(2,745)
Observations	2724	2764	5044	1183
Bandwidth Size	5.340	5.458	10.68	2.670
Bandwidth Type	CCT (h)			

Notes: The dependent variable criminal is a dummy that that equals 1 if the criminal candidate won and 0 otherwise. The outcome measured is the annual number of 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. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

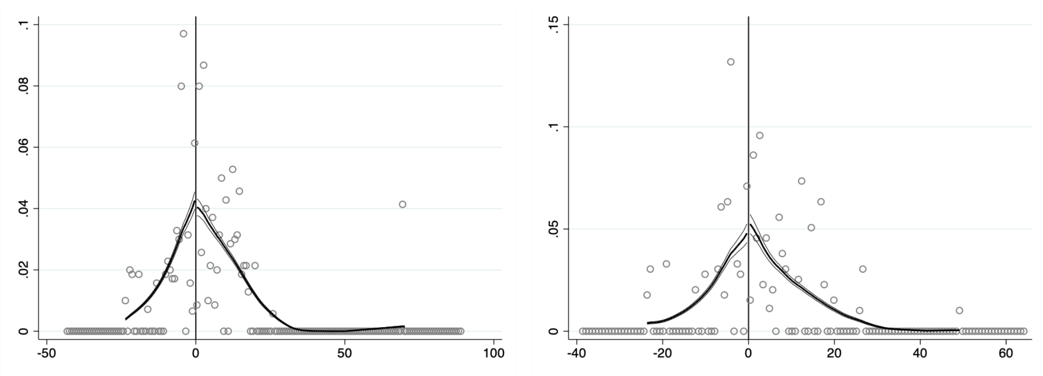
Table C.13: RD Specification with Covariates

	(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 outcome measured is the annual number of projects per 1000 residents. In Panel B, the outcome measured 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. The 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). Asterisks denotes 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 from that of a clean candidate. Positive values indicate the difference between the vote share received by a criminal winner less that of a clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less 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 Constituency Characteristics (Serious Criminals Only)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Partisan	SC/ST Reserved	Log Total Votes	Voter Turnout	Log Electoral Size
Criminal	0.083	-0.422	0.017	-2.446	-0.011
	(0.364)	(0.275)	(0.056)	(2.053)	(0.067)
Observations	2417	2982	2292	2212	2322
Bandwidth Size	7.174	9.743	6.331	6.079	6.393
Method			Local Linear		

Notes: The dependent variable criminal is a dummy that equals 1 if the serious criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2: Balance of Candidate Characteristics (Serious Criminals Only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Log Income	Log Liabilities	Age	Gender	High School Degree	Incumbent	National Party
				Panel A: Winner			
Criminal	-0.341	0.893	-3.665	0.108	-0.044	-0.041	0.011
	(0.867)	(3.724)	(4.863)	(0.072)	(0.250)	(0.089)	(0.060)
Observations	2357	3047	2212	1622	3719	1877	2212
Bandwidth Size	7.138	9.823	5.931	4.554	7.746	4.920	5.945
				Panel B: Runner-up			
Criminal	0.842	0.169	0.160	-0.183	0.180	-0.015	0.011
	(0.768)	(3.676)	(5.491)	(0.159)	(0.141)	(0.260)	(0.060)
Observations	2982	2357	2357	2322	2212	1812	2212
Bandwidth Size	9.402	6.731	6.787	6.409	6.011	4.838	5.945
Method				Local Linear			

Notes: The dependent variable criminal is a dummy that equals 1 if the serious criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Balance of Constituency Characteristics (Corrupt Criminal Only)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Partisan	SC/ST Reserved	Log Total Votes	Voter Turnout	Log Electoral Size
Criminal	-0.066	-0.649**	-0.016	-2.750*	-0.063
	(0.347)	(0.324)	(0.072)	(1.498)	(0.083)
Observations	1476	1781	1476	1781	1441
Bandwidth Size	6.971	8.571	6.774	8.795	6.552
Method			Local Linear		

Notes: The dependent variable criminal is a dummy that equals 1 if the corrupt criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Balance of Candidate Characteristics (Corrupt Criminals Only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Log Income	Log Liabilities	Age	Gender	High School Degree	Incumbent	National Party
				Panel A: Winner			
Criminal	-0.374	-0.654	-8.250	0.023	-0.044	0.130	-0.01
	(0.784)	(5.882)	(5.350)	(0.031)	(0.250)	(0.136)	(0.084)
Observations	1781	1441	1781	954	3719	1721	1441
Bandwidth Size	8.572	6.520	8.511	4.091	7.746	8.283	6.235
				Panel B: Runner-up			
Criminal	1.351	-2.336	4.599	-0.290	0.043	0.262	-0.010
	(1.085)	(4.621)	(6.398)	(0.204)	(0.284)	(0.348)	(0.084)
Observations	1836	1441	1781	1441	1356	1321	1441
Bandwidth Size	11.16	6.231	8.888	6.169	5.989	5.336	6.235
Method				Local Linear			

Notes: The dependent variable criminal is a dummy that equals 1 if the corrupt criminal candidate won and 0 otherwise. Standard errors are clustered at the constituency level and given in parentheses. The 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). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E. Candidate Affidavits

Figure E.1: Example of Candidate Affidavit

Sl.No........62/16

भारतीय गैर न्यायिक

बीस रुपये

रु.20

Rs.20

TWENTY RUPEES

भारत

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 :- 1) Asansol (south) PS: 164/2006 (GR 840/2006) 2) Asansol (South) PS: 276/95 3) Hirapur Ps : 158/2009 dt 19/01/2009 4) Asansol (South) PS: GR 1599/96;321/96 Ltd SDJM Asansol: - 1)Asansol (south): 9/93 (GR 43/93) 2) Asansol GRPS :-65/90 dt 28/05/1990 Ltd. ACJM In-charge:- 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. Sections of the Act and description of the offence for which cognizance taken: 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 2) Asansol (south) PS-276/95 : U/S 148/149/323/516 IPC 3) Asansol(south)-164/2006; U/S 143/447/427/186/353/ GR-840/2006 4) Asansol (South)- 09/93;u/s147/148/149/353/323/427/435 IPCV 5) Hirapur PS—158/2009; u/s 143/342/352/86/353 IPC 6) NGR 816/2004; GDE No.- 1293/2014 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.