

The Consequences of Electing Criminal Politicians on India's Largest Workforce Program*

Abhinav Khemka[†]

This is a preliminary draft. Please do not cite or distribute.

Abstract: Voters despite having the option to reject corrupt or criminal politicians often fail to do so. In this paper, I argue that in contexts with weak institutions and widespread corruption allows such politicians to manipulate the system in delivering state resources to their constituents perhaps explaining their continuous electoral success. 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 on average criminal constituencies observe an annual reduction in the project completion rate by 67% in comparison to the average clean constituency. In contrast, constituencies that barely elect a criminal politician observe a rise in work allocation by 36% annually in comparison to constituencies where they barely lost. These results seems to be driven by clientelistic distributive strategies where criminal politicians systematically provide targeted benefits to voters which might explain their willingness to support them.

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

JEL codes: D72, D73, H53,O12

*I am thankful for the valuable comments from Jordi Munõz, Pilar Sorribas-Navarro and the participants of workshops at University of Barcelona.

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

1 Introduction

The electoral success of corrupt or criminal 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 of supporting candidates of disrepute. Why do voters despite having the option to do so fail to “throw the rascals out”?

Although the literature before provides various explanations for this paradox, a dominant argument often made is that this purely an information constraints problem. This argument holds that voters generally have a distaste towards corruption or criminality but fail to punish them simply because they lack the awareness to do so. Thus, when presented with credible information, voters would be reject such candidates (Ferraz & Finan, 2008; Winters & Weitz-Shapiro, 2013). However, recent research has shown that even in contexts where the voters are knowledgeable about the candidates acts of wrongdoing they might be willing to support them at the ballot (Banerjee et al., 2011; Boas et al., 2019).

A counter argument 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 exchange votes for particular benefits explaining their willingness to excuse venal politicians. Scholars have argued that this phenomenon is most prevalent in settings where government institutions are weak and the state is unable to fulfil its basic responsibilities (Easterly & Levine, 1997; Stokes, 2005). Such conditions allow clientelistic networks to prosper perhaps explaining why citizens might support corrupt politicians. Despite there being some literature linking corruption or criminality to clientelism (Manzetti & Wilson, 2007; Vaishnav, 2017), there a lack of hard empirical evidence.

Previous research has mostly focused on the overall performance of corrupt or criminal politicians and have found substantial negative cost on economic development (Bardhan, 1997; Prakash et al., 2019), various components of the economy such as household consumption (Chemin, 2012), private sector investment (Nanda & Pareek, 2016) and a decrease in government trust (Ares & Hernández, 2017). However, these studies look only at aggregate measures of economic activ-

ity and shed little light on how the election of low quality candidates might impact the delivery of state resources. In this article, I aim to fill this gap in literature by investigating the effect of electing candidates accused of wrongdoing on specific policy measurements.

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. Rather than concentrating their efforts on overall economic activity, these politicians leverage their reputation and access to wealth to strategically deliver benefits to their constituents which they can claim credit for and strengthen clientelistic relationships. By manipulating the access to specific public resources, they are effectively able to convey to voters that criminality serves as a positive signal of competence explaining their continuous electoral success.

To test this theory, I examine the effects of electing criminal politicians on the delivery of the state resources in the context of India. The Indian case provides an ideal setting to examine this hypothesis for several reasons. Despite holding massive free democratic elections with multiple parties, politicians accused of criminality are elected frequently at all levels of government and this number is steadily rising over time. In 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 24% in 2004.¹

With an environment where access to resources are heavily mediated with middle-men and there is a lack of proper institutions makes India a potential scenario for clientelistic networks to thrive. A large body of ethnographic literature on India shows that citizens view criminal politicians as having the ability to “get things done” or “Robin Hood” figures (Berenschot, 2011a, 2011b; Vaishnav, 2017; Martin & Michelutti, 2017). These scholars theorise that the inability of the formal state to deliver public goods allows criminal politicians to step in and fulfil the basic needs of citizens and build clientelistic relationships explaining why voters tend to support them. Despite the availability of rich qualitative accounts, there is no formal estimates showing if criminal politicians perform better in terms

¹The data on candidates criminal records is collected from Myneta an open data platform run by Association for Democratic Reform (ADR). Retrieved from <https://myneta.info>.

of delivering public goods there constituents.

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. With a budget of about 900 billion Rupees (approximately 10 billion US\$) in 2021-22, MGNREGA provides employment to about 113 million households, making it not only the largest workforce program in India but in the world.² In addition to employment generation, the program aims to improve village infrastructure (e.g., roads, toilets and canals). To date, over 50 million local infrastructure projects have been completed under the scheme.

I take advantage of the Indian Supreme court judgement in 2003 mandating all political candidates contesting at both the national and state elections to submit a sworn affidavit disclosing information on their criminal background. Leveraging the data from these affidavits, I test if the election of a Member of 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.

I concentrate on these two outcomes since the program aims at generating rural employment and improving local infrastructure. This provides the perfect backdrop to test the theory if criminal politicians strategically distribute resources to their constituents. I expect to find that criminal politicians have negative effects on Projects Completed since it provides ample opportunities for rent-seeking and is harder for criminal politicians to claim credit for. On the other hand, I expect that criminal politicians either improve or at the very least do not have adverse effects on the number of Work Days since this directly affects voters reducing their likelihood of re-election.

One potential concern 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 constituency over others. To overcome

²The data on the program is available on the national MGNREGA public data portal. Retrieved from <https://MGNREGAweb4.nic.in>

this endogeneity problem, I use a regression discontinuity (RD) design, comparing constituency 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 constituency should be close to random (Lee & Lemieux, 2010). The use of this methodology is not novel to this study and several works previously have used a RD design in evaluating several outcomes in the context of Indian elections (Chemin, 2012; Prakash et al., 2019).

Using this setup, I test the effect of electing a criminality accused politicians on MGNREGA in the state of the West Bengal during the 2011 to 2020 period. I focus on West Bengal since it is one of the better performing states in terms of allotting jobs and utilising funds under MGNREGA (The Hindu, 2018). The program often suffers from implementation issues leading to substantial variation in access across Indian states.³ Thus, by using data from West Bengal insures the estimates in this paper are at the lower bound. Additionally, West Bengal is a plausible setting for political networks to play a role because the program is economically and politically salient.⁴

The main findings of this paper show that criminal politician have substantial effects on the delivery of MGNREGA in the constituency they are elected in. In particular, the election of criminal politician leads to average annual fall in the number of Projects Completed by 67% and an average rise in the work allocation by 36% annually in comparison the average clean constituency. I further find the delivery of the program varies by constituency characteristics. The negative effect in the number of Projects Completed is concentrated only in constituencies where the criminal candidate belongs to parties non-aligned to that of the state government. In contrast, criminal politicians perform better in terms of providing work regardless of political alignment. Additionally, I find that that the delivery of MGNREGA outcomes differs significantly if the constituency is reserved for

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

⁴West Bengal displays a high demand for work with more than 95% of the villages applying each year for new projects and more than 50% of the rural population being employed under the scheme.

Schedule Caste/Tribe (SC/ST).⁵ While the election of criminal candidates leads to a drop in the number of Projects completed regardless of the reservation status, the positive effect in Work Days is concentrated in non-reserved constituencies. These results strongly support the argument that criminal politicians might be more inclined to strategically deliver targeted resources when they are potential electoral benefits on offer.

Next, I explore the underlying mechanisms that could potentially be driving these results. In particular, I investigate if criminal politicians are actually better at providing higher work allocation to their constituents or this can be explained 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, the results show that in constituencies that barely elect criminal politicians spend significantly larger portion on the labour component of the program rather on the materials. Since material expenditure is often the portion which provides opportunities to engage in rent-seeking activities (Olken, 2007), these results seem to suggest that criminal politicians systematically target the wage dimension to use as a tool to strengthen clientelistic relationships 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, more narrowly, the results in this paper bridges the gap between the two competing strands of literature on India: one that using qualitative field work 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). I find that although criminal politicians reduce overall program efficiency, they do not necessarily have negative effects on specific outcomes. Instead, when the criminal politician is electorally motivated they can use their criminal networks and reputation in moving the bureaucratic wheel to divert targeted resources to their constituents.

⁵The Indian government randomly picks one-third of the constituency seats to be reserved for SC/ST category. Only candidates belong to these caste groups may contest from these seats.

Second, as per my knowledge, this is the first study that examines the impact of electing criminal politicians on program service delivery in developing world context. Although this paper concentrates on the Indian case, criminal politicians are not limited to India.⁶ Thus, these findings might of relevance to various developing countries that are struggling with similar situations.

Third, this paper contributes to the ever-growing literature trying to explain why voters persistently elect criminal politicians in democratic countries. The existing literature provides several explanations why voters fails to punish bad quality politicians at the ballot such as lack of adequate information (Ferraz & Finan, 2008), ethnic voting (Banerjee & Pande, 2007), patronage (Kitschelt & Wilkinson, 2007) or 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 the candidate's criminality can sometimes serve as a positive credibility cue. Under such conditions, voters might be rationally rewarding criminality because they believe this to be a necessary attribute in politics.

Lastly, this paper adds to the broader distributive politics literature. Although there is some evidence at the aggregate level that criminal or corrupt politicians are more likely to manipulate government resources and deliver targeted benefits to build clientelistic networks (Manzetti & Wilson, 2007), there is little evidence on this theory at the granular level. Previous works have mostly focused on how politicians use distributive strategies in allocating resources according to partisanship (Stokes et al., 2013) or targeting specific groups (Kitschelt & Wilkinson, 2007). However, the literature lacks in providing any evidence on how candidate quality can influence clientelistic strategies. I contribute to this literature by providing the first statistically significant and meaningful evidence showing how candidate quality can have substantial effects on the delivery of public resources.

The rest of the article is structured as follows: Section 2 provides the argument. Section 3 and 4 discusses 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.

⁶Several developing countries have reported a rise in criminal politicians being elected to office such as (but not limited to) Brazil, Indonesia, Pakistan, Philippines and Nepal.

2 The Argument

I argue that in contexts where corruption is widespread and there is lack of state capacity, criminal politician strategically provided targeted benefits to their constituents to further strengthen clientelistic relationships. This is especially relevant in the context of developing countries where access to resources is scarce and heavily mediated with corrupt actors which can lead to citizens to show a willingness to exchange votes for public goods.

The argument I propose has several theoretical and empirical foundations. Previously scholars have argued that weak institutions allow corrupt politicians to manipulate the system and use the delivery of public goods as a mechanism to buy votes (Stokes, 2005; Manzetti & Wilson, 2007). These scholars theorise that if corrupt politicians are better at providing resources, citizens might vote for them at the ballot even though they are corrupt.

Vaishnav (2017) in his seminal work on understanding the nexus between criminals and politics in India goes even one step further and theorises that criminal politicians might be significantly better over other politicians when it comes to delivering resources and protecting the rights of citizens.⁷ He argues that criminal politicians have broadly three potential channels which provides them with a comparative advantage. 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.⁸ They can use this cash not only to run expensive election campaigns but in paying financial bribes necessary to move the bureaucratic wheel. Second, criminality can be understood by some citizens as a signal of the politician being effective strongmen who are willing to go above the legal means to protect the right of citizens and influence the distribution of resource. Criminal politicians can use this reputation as a tactic to show a willingness to “flex his muscles” or the perception that they are able to do so in intimidating or coercing bureaucrats in diverting resources to their con-

⁷Several other scholars across India using ethnographic and qualitative research find that criminal politicians are viewed as effective strongmen who can act in the best interest of citizens. See Berenschot (2011b, 2011a); Witsoe (2012); Martin and Michelutti (2017).

⁸ADR (2022). “What explains the increasing entry of criminals and wealthy candidates into politics?”

stituencies. Lastly, in developing countries control over resources requires strong ties with middlemen, bureaucrat and other local leaders. In this respect, criminal enterprises often generates employment and rent-seeking opportunities for all these state actors fostering strong networks. In turn, the criminal politicians are able to activate these networks to manipulate the system to provide targeted benefits to their constituents. Thus, these explanations provide a clear intuition on the attributes that a criminal politician might possess to divert public goods to their constituencies.

In this respect, development programs such as MGNREGA provides an ideal backdrop to test if criminal politicians actually deliver. First, empirical studies have found that the delivery of MGNREGA can significantly influence election outcomes. Indian elections are highly competitive and welfare schemes are often used as instrument to win elections.⁹ This is due to the fact that MGNREGA is implemented the village level and local politicians can often claim credit for its delivery (Gulzar & Pasquale, 2017). Second, the program aims at generating rural employment by providing minimum wages which leads to self-targeting of the poor. There is a general agreement in literature that clientelism is more likely to be stronger among the poorest and least educated voters (Kitschelt, 2000; Stokes et al., 2013). Since these segments of society have more immediate needs, they might be more prone to overlook probity for the short-term benefits on offer. This provides an ideal prospect for criminal politician to target these type of voters and further strengthen clientelistic relationships. Lastly, the money available under the MGNREGA is considerable, even exceeding the discretionary funds of the MLA, making this the best vote-buying tool at their disposal to connect with their voters.¹⁰ In short, if criminal politicians are truly better suited to “get things done”,

⁹Zimmermann (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 own party 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.

¹⁰Each MLA in West Bengal has a annual budget of 5 crore Rupees (600,000 US\$ approximately) to spend at their discretion for local area development (MLAADS). In comparison, the MGNREGA budget can be significantly larger depending on the region. For example, in the sample constituency, the average total expenditure incurred on the program was about 14.1 crore Rupees (1.6 million US\$ approximately), out of which about 76% was spent on wages.

we should expect this to be prominent when comparing between criminal and clean politicians in a program of MGNREGA's importance.

To further substantiate the argument that criminal politicians are solely driven by electoral motives, I examine if the delivery of the program varies by constituency characteristics. First, I investigate if there are discrepancies in the delivery of MGNREGA outcomes if the candidate belongs to the same party as that of the state ruling government. Previous literature highlights that political leaders might target politically aligned constituencies to expand their political networks and improve clientelistic relationships with their core voter base (Dey & Sen, 2016; Dasgupta, 2016). On the other hand, aligned constituencies often have better access to resources which increases the probability of rent-seeking opportunities on offer (Arulampalam et al., 2009). Hence, if criminal politicians are motivated by corruption, we should expect it to be more prevalent in partisan constituencies. Conversely, if criminal politicians aim to strengthen their chances of re-election, we should expect them to perform significantly better in such constituencies.

Second, I examine if there is any effect of MGNREGA's delivery depending on the constituency reservation status. Seats reserved for SC/ST category often observe candidates with less experience being selected to office due to lower electoral competition (Chattopadhyay & Duflo, 2004). MLAs running from reserved seats are unlikely to be re-elected which might prompt them to engage in corrupt practices due to lack of accountability or fear of voter backlash (Finan & Ferraz, 2011). Thus, if criminal politicians only care about delivering resources to their constituents when they are electoral gains to be had, the delivery of program could differ depending on the constituencies reservation status. Since the Indian government randomly reserves these seats, it allows a direct estimation of the causal effects that reservation might have on MGNREGA outcomes.

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 works project. With nearly 70% of India's population living in rural India, MGNREGA is the largest anti-poverty program in the country and the largest rural workfare program in the

world. While any household can apply for the scheme, the program pays minimum wages, leading to “self-targeting” of poorer households. In addition, the program aims to improve local village infrastructure such as ditch irrigation and unpaved road building.

The implementation of MGNREGA is highly complex and the Ministry of Rural Development (MoRD) provides a detailed 232 page document providing a comprehensive guidelines for implementation, execution and rights under the program.¹¹ I highlight a few of the key features of the program below.

The implementation of MGNREGA involves institutions at the central government and state level, and at all three tiers of rural government in India known as the *Panchayat Raj* Institution (PRI): *Zilla Parishad* at the district level, the *Panchayat Samiti* at the block level, and the *Gram Panchayat* (GP) at the village level. Since the program is highly decentralised, the principal authorities for the implementation of the MGNREGA is under the control of the PRI and the request of work days and project approvals flow up the administrative chain and funds flow down from the central or state government to the GPs and eventually into 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 for 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 scrutinises 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 discuss and approve the Block Plan and forward 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 of labour to be generated, and (3) the full cost. This plan is forwarded to the *Zilla Parishad* which

¹¹For 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.

discusses and provides final approval for all the projects under MGNREGA 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 registering households, issuing job cards, allocating employment, initiating MGNREGA related projects and, measuring and evaluating the project status.

In terms of funding, MGNREGA is financed from both the central and the state government. The central government covers 75% of the material and wage expenses for semi-skilled and skilled workers and 100% of the wage costs of unskilled workers. The state government is mandated to provide the funds for the remaining 25% of expenses. Additionally, 60% of the total expenditure on projects must be spent on wages and the rest 40% on materials. Both the central and state government directly release the funds to the district and after approval of plans these funds are sent to the GP. 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.

MGNREGA provides ample opportunities for the MLAs to influence the implementation and allocation of resources at different levels of the administrative chain. Although officially the execution of the program is in the hands of the village level government, the MLA can manipulate the program at various stages. 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 pressurise 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 various 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 nation level and the second largest number of state assembly seats. Electorally, the West Bengal state government like the rest of India follows a parliamentary form of government. The legislature is divided into two main branches: *Vidhan Parishad* (Upper House or Legislative Council) and *Vidhan Sabha* (Lower house or Legislative Assembly). Members of the state assembly are referred to as Members of Legislative Assembly (MLAs), with those at the *Vidhan Parishad* being elected by nomination from state legislative members for six years, and those at the *Vidhan Sabha* being elected by the people for five years unless dissolved by the President on the advice of the council of ministers. MLAs are elected from single-member constituencies using the first-past-the-post voting structure with an allowance for coalitions if no majority is attained by a single party.

As the rest of the country, 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 much recently. In 2003, the Indian Supreme court in a landmark judgement 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 their criminal record. Remarkably, the release of these affidavits revealed that criminal politician were regularly elected to office and this number has been steadily rising over time. 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. This problem is not limited to West Bengal

politics and similar trends can be observed all across the countries where criminal politicians are elected to political office consistently at both the national and state level.

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 incentivises 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 cognisant about the problem and the recent uptake of criminal politicians has been frequently debated in the Indian parliament but no serious actions have been taken. Consequently, in 2018, the Indian Supreme Court instructed the parliament to make a law that at the minimum prevents candidates accused of serious crimes to contest 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. Subsequently, the Supreme Court showing great concern about the “criminalization” of Indian politics made a ruling in 2020 that mandated political parties to highlight the candidates’ criminal records on their social media platforms in various vernacular languages. Although the law aimed at providing more information to voters, it has had little effect in curbing 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 held in 2011 and 2016 is collected from the Trivedi Centre for Political Data (TCPD). In total, 3684 candidates contested from 572 election races across the two election cycles. The sample size is further restricted to only mixed election races where one of the top two candidates had a criminal accusation against them providing a sample size of 249 election races. Lastly, certain of the constituencies lie in urban

areas and do not qualify for the MGNREGA scheme.¹² Thus, I drop them from the analysis providing a final sample size of 142 elections races.

The main variable of interest is the criminal accusations of the political candidates. Originally, the candidate affidavits are available on the ECI website as PDFs forms. Association of Democratic Reform (ADR), an organisation created as an election watchdog has re-entered and compiled this data making it freely available to public on their social media platform to provide better access and improve political accountability.¹³ In the baseline specification, I define a binary variable which equal to 1 if the politician is accused of any criminal charges and 0 otherwise.

To further explore the robustness of 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, political rivals are incentivised to make false accusations to gain an electoral advantage (Prakash et al., 2019).¹⁴ 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, we should expect that type of crime matters. For example, a politician accused of common theft might significantly differ from a politician accused of murder. Thus, certain types of charges should have stronger treatment effects. For this purpose, I use the definition provided by ADR that classifies serious crimes according to nature of crime and sentencing period.¹⁵ Then, I look at the effect of corruption charges on MGNREGA outcomes. I use the definition provided by Prakash et al. (2019),

¹²MGNREGA is a village level program only applicable in rural areas. To insure that the constituencies are similar in nature, I consider only constituencies that have a minimum rural population of above 100,000.

¹³ADR has created a dedicated website call MyNeta that provides data on the candidates party affiliation, education, age, assets, liabilities and criminal record: <https://myneta.info>.

¹⁴Several studies have used the data on criminal allegations against politicians in India and have found no evidence that suggest that these allegation are false. For example, see Vaishnav (2011); Prakash et al. (2019).

¹⁵Explanation 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>.

who consider corruption charges as the ones that lead to a financial loss to the government.¹⁶

Table B.1 and Table B.2 provide the distribution of candidates by number and type of criminal charges respectively. We can clearly observe that the number of criminal candidates seem to be largely concentrated at the top. From total candidates 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 for the period of 2011-2021. 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, type and status of projects and the expenditure incurred. Since the main objective of the program is to improve local infrastructure and provide rural employment, I consider two main outcomes: number of Projects Completed and the number of Work Days in each constituency year. Additionally, to account for any variation in population these 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 due the fact that in India the administrative units (such as districts, blocks) does 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 of 2001 to map assembly constituencies.

¹⁶Prakash 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>.

The original delimitation orders are available on the ECI website in PDFs forms. To insure 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.

6 Empirical Strategy

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

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

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 which equals to 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 during 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 clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less that of

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 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 ($h/2$).

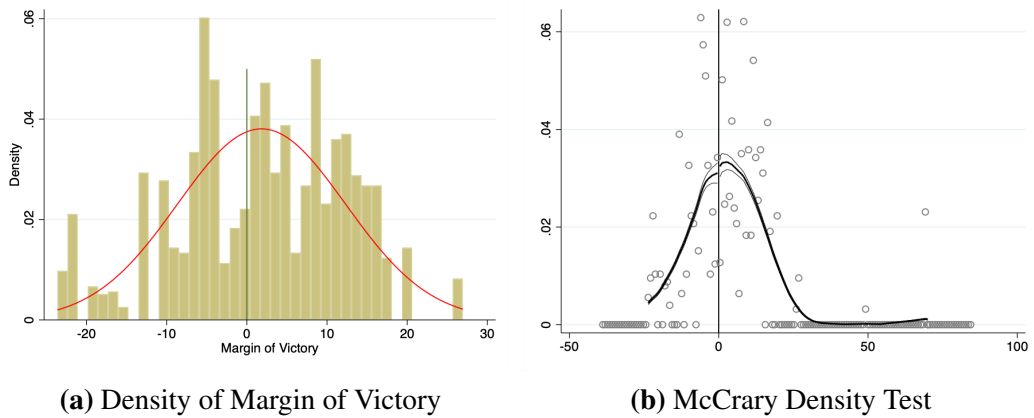
7 Results

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, I conduct a McCrary (2008) density test provide in Figure 1(b) that confirms the density of the running variable is similar below and above the cut-off. As an additional check, I run the density test proposed by Cattaneo et al. (2018) and find no statistical evidence of manipulation of the running variable.

The second main assumption of the RD design is that the observable and unobservable 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. A description of the constituency and candidate profile is provided in Table B.3 and Table B.4 respectively. Out of the total 142 constituencies, 53 belong to control group and 89 to the treatment group. Although due to lack of data availability it not possible to check for every characteristic, the treatment group have a fewer

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



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

number of constituencies that are reserved, co-partisan and have a lower average rural population.¹⁷ In terms of the candidate profile, the data looked mostly balanced for a range of characteristics across both the control and treatment groups.

More formally, a balance test for several constituency characteristics such as whether the constituency belonged to the state ruling party, is SC/ST reserved, the total votes casted in logs, voter turnout and the total electoral size in logs, and candidate attributes such as their income and liabilities in logs, age, gender, whether they attained a high school degree, incumbency status and if the candidate belongs to a nation party is provided in Table 1-2 and provide no statistical evidence of imbalances. Thus, these diagnostic checks put together provide sufficient evidence for the use of a RD design.

¹⁷To account for this, I test the robustness of the results by including controls for various constituency level characteristics. The results of this exercise are provided in Table C.10 and remain qualitatively similar to the main findings.

Table 1: Balance of Constituency Characteristics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Ruling Party	SC/ST Reserved	Log Total Votes	Voter Turnout	Log Electoral Size
Criminal	-0.097 (0.358)	-0.256 (0.317)	0.0169 (0.069)	-0.539 (2.515)	0.031 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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 used is 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 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 (0.769)	-0.168 (3.957)	-6.673 (5.256)	-0.101 (0.176)	-0.030 (0.263)	-0.119 (0.111)	0.095 (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 (0.805)	0.501 (3.678)	-1.102 (4.877)	-0.065 (0.123)	-0.018 (0.139)	0.001 (0.233)	0.095 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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 used is 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 candidates, while a negative margin of victory implies that the criminal candidate lost and the non-criminal won. The vertical line represent 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 discontinuity implying that at the threshold, constituencies that elect a criminal politician complete fewer number of projects per 1000 capita in comparison to constituencies that elect a clean candidate. In contrast, 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 generate higher work allocation per 1000 capita when compared to constituencies that elect a clean MLA.

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 completes 5.26 fewer projects per 1000 residents in comparison to constituencies where the criminal politician barely lost. These magnitudes are substantial. To put this in context, the sample treated median constituency comprises of about 240,000 residents implying that a criminal politician completes on average 1260 less projects annually relative to the mean value for the non-treated constituency close to the threshold. Likewise, in the RD sample an average non-treated constituency has a project completion rate anywhere between 7.9 and 21.5 projects per 1000 capita which means that criminal constituencies observed a drop of 67% to 27% in work completion rate in comparison to the average clean constituencies. Also note that these estimates are yearly meaning

that during a full constituency term of five years a criminal politician can have extremely large impact on generating assets under the scheme. For robustness, I generate the estimates using several alternative bandwidths in column (2)-(4). In column (2) I use the IK bandwidth and in column (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 but still remains highly significant and meaningful. While halving the bandwidth in column (4) increases the magnitude.

When looking at Work Days in Panel B, the results show that a constituency that elects a criminal MLA observes a rise of 1295 Work Days per 1000 residents when compared to constituencies that elect a clean candidate. Like before, in a median treated constituency, a criminal MLA generates nearly 310,800 additional Works Days in comparison to the median non-treated constituency close to the threshold. This estimate reflects to about 36% rise in annual Work Days in a constituency where a criminal politician won when compared to the average clean constituency. 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 reduces but still remain quantitatively and statistically significant. Finally, halving the bandwidth in column (4) the estimates loose statistical power.

To provide further perspective of these findings, I estimate the effects of electing criminal politicians on the labour 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 constituencies that barely elect a clean politician. Again these magnitudes are huge: comparing with the median non-treated constituency, a criminal MLA spends about 46.34 million Rupees (550,000 US\$) more on labour expenditure annually than a clean MLA. On average, the annual cost of a project cost ranges between 0.15 million Rupees (1,800 US\$) and 0.46 million Rupees (5,600 US\$). This means that if the criminal politician allocated these extra funds spent on wages efficiently it could have been potentially used to complete anywhere between 101 to 309 projects annually. The implied returns are

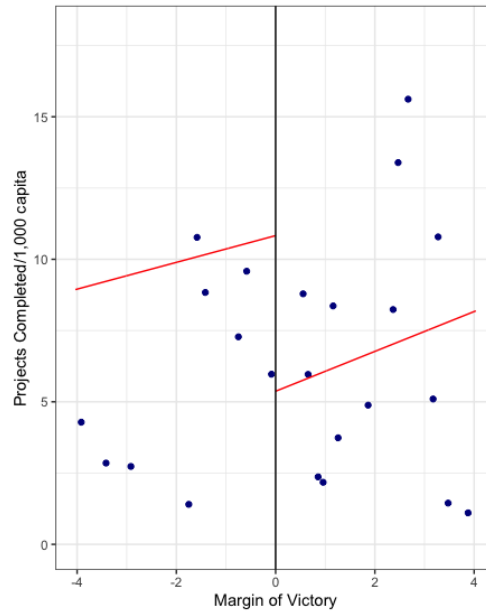
so high that despite the fact that criminal politicians generate more employment for their constituents, they clearly seem to reduce overall welfare significantly.

Table 3: Effect of Electing Criminal Politicians on MGNREGA

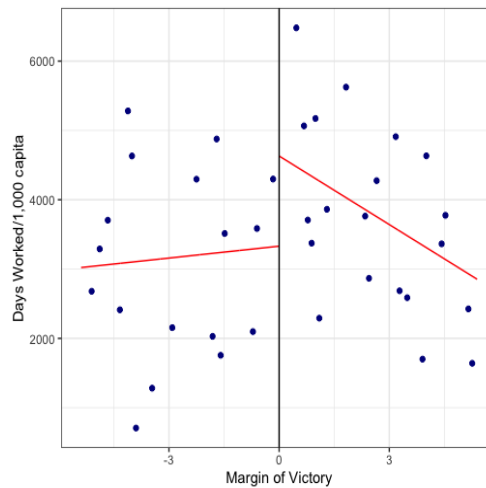
	(1)	(2)	(3)	(4)
Panel A: Projects Completed/1000 capita				
Criminal	-5.264*** (1.313)	-5.504*** (1.879)	-3.436*** (1.205)	-6.440*** (2.138)
Observations	2459	1492	4679	1118
Bandwidth Size	4.916	3.407	9.832	2.458
Panel B: Work Days /1000 capita				
Criminal	1,295*** (477.3)	1,309*** (470.6)	1,147*** (333.4)	746.2 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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 numbers of Work Days 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: Effect of Electing Criminal Politicians on MGNREGA



(a) Projects Completed



(b) Work Days

The forcing variable is the margin of a victory that measures the difference between 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 clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less that of 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 numbers of Work Days per 1000 residents. In both figures the x-axis represents the margin of victory. The scatter plot represents the evenly spaced mimicking variance (esm) number of bins using spacings estimators. The RD estimates are based on a local linear regression using a triangular kernel. The optimal bandwidth used is a mean squared error optimal bandwidth selector proposed by Calonico et al. (2014). Both model include year fixed effects and the standard errors are clustered at both the gp and constituency level.

Table 4: Effect of Electing Criminal Politicians on MGNREGA Labour Expenditure

	(1)	(2)	(3)	(4)
	Labour Expenditure/1000 capita			
Criminal	193,118*** (62,455)	186,256*** (70,727)	171,649*** (44,093)	155,489 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. The outcome measured is the total labour expenditure per 1000 residents. The RD estimates are based on a local linear regression using a triangular kernel. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.3 Heterogeneous Effects

Till now, the estimates provided has focused on the average cost of electing criminal politicians. However, this effect might vary at the constituency level depending on various observable characteristics.¹⁸ In the first specification, I test if partisan alignment has any impact on the delivery of MGNREGA outcomes. 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 Table 5 presents the esti-

¹⁸Several studies have pointed out that the estimation of heterogeneous treatment effects is not straight-forward in RD designs. I follow, the methodology proposed by Cattaneo et al. (2023) to split the sample and conduct the analysis at the subgroup level. The authors show that as long as the covariates are discrete, there is no additional assumptions or validity tests required. However, since splitting the sample reduces the number of observations in each group, one limitation of this procedure is that the estimates might suffer from reduced statistical power.

¹⁹For example, Das and Maiorano (2019) find that in the state of Andhra Pradesh, the state ruling party often spend 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 labour is significantly larger in areas where the ruling party barely won versus areas in which they barely lost.

mate of this exercise. In column (1)-(2), the results clearly suggest the effect is concentrated in constituencies belonging to the non-ruling party. Although both ruling and non-ruling constituencies seem to generate more Work Days, the negative effect on the number of Projects Completed is driven only by constituencies where a non-partisan criminal won. These findings are consistent with the literature which has found that ruling parties maximise their electoral advantage and perform better in partisan constituencies further consolidating their core voter base (Asher & Novosad, 2017).

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 the electoral rewards from being elected to office. Thus, it is worth investigating how the effects vary by the reservation status of constituency. Looking at column (3)-(4), we can observe that criminal politicians have a negative effect on the number of Projects Completed regardless of reservation status, albeit the magnitude is larger for reserved constituencies. In contrast, the results suggest that criminal politicians have a positive effect on the number of Work Days generated under MGNREGA only in non-reserved constituencies.

These findings are along the lines of the previous works that have looked at the effects of reservation on policy outcomes. Since in reserved constituencies the incumbent often observes a lower probability of re-election (Afridi et al., 2017), it makes sense that the elected politician is less motivated to provide resources to their constituents. In the same vein, due to lower electoral competition, candidates that are less experienced often win in reserved seats (Chattopadhyay & Duflo, 2004), which could perhaps explain why reserved constituencies observe a larger drop in the number of Projects Completed in comparison to non-reserved ones. Thus, these results put together seem to suggest that the electoral motives of the politician can have telling implications on the delivery of the program. However, one concern is that since the sample size is relatively small, these estimates might suffer from lower statistical power.

Table 5: Effect of Electing Criminal Politicians by Constituency Characteristics

	(1)	(2)	(3)	(4)
	Non-Ruling	Ruling	Non-Reserved	Reserved
Panel A: Projects Completed/1000 capita				
Criminal	-10.95*** (1.763)	-0.452 (2.618)	-4.435** (2.239)	-5.375*** (1.959)
Observations	832	660	2594	520
Bandwidth Size	3.280	4.075	7.626	3.584
Panel B: Work Days/1000 capita				
Criminal	1,891*** (533.9)	1,167* (647.7)	2,717*** (561.8)	-759.8 (1,149)
Observations	1527	1657	1327	415
Bandwidth Size	5.141	7.810	4.043	2.745
Bandwidth Type	CCT (h)			
Method	Local Linear			

Notes: The dependent variable criminal is a dummy that equals to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. The model includes 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 used is a mean squared error optimal bandwidth selector proposed by Calonico et al. (2014). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.4 Mechanisms

The results in this paper show that the election of criminal politicians have 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 the findings stems from criminal politicians indulging in corrupt practices or employing strategic tactics to provide

targeted benefits to their constituents. To test this hypothesis, below I estimate several measurements which might 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 of 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 6 provides the estimates for this specification. In both Panel A-B, the estimates provide no statistical evidence of any average expenditure differential between criminal and clean constituencies.

²⁰The data only provides the reported material expenditure and there is no way 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.

Table 6: Effect of Electing Criminal Politicians on MGNREGA Average Cost

	(1)	(2)	(3)	(4)
Panel A: Wages per WorkDay				
Criminal	0.538 (7.054)	0.675 (7.032)	3.484 (4.974)	11.10 (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 (25,657)	-6,442 (21,711)	-1,911 (19,973)	28,749 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Second, I measure if there any deviation between the mandated 60:40 material-labour expenditure rule between criminal and clean constituencies. As discussed earlier, MGNREGA stipulates that 60% of expenditure must be spent on labour and the remaining 40% on materials. This law is suppose to ensure that areas do not differ in terms of the number of durable assets created and the number of work days offered under the scheme.²¹ If criminal politicians were partaking in corrupt

²¹MGNREGA have strict guidelines on the types of projects that can be undertaken and must maintain a 60:40 labour-material ratio but due to lack of proper monitoring this rule is not always adhered to.

practices, they should take advantage of this lack of monitoring 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.²² Second, the material component provides the only potential source for embezzling funds in the program. For example, a study by Afridi and Iversen (2013) using social audit reports find substantial irregularities in the material expenditure of the program.²³ This problem has been further exacerbated by the introduction of direct wage payments into the beneficiaries bank accounts in 2008. Although 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 the politician is mainly driven by amassing wealth either by rewarding contractors or stealing, we would expect them to rather put their efforts on the material dimension of the program than on labour expenditure.

Table 7 provides the estimates of this specification. In particular, the outcome measured is the proportion of the total expenditure spent on material less the 40% mandated requirement. In column (1), we can clearly see that criminal politicians spent significantly less on the material component than the legal requirement. Constituencies that barely elect criminal politicians observe a drop in material expenditure by 7.20% less than the required threshold in comparison to constituencies where criminal politician barely lost. In column (2)-(4), the estimates mostly remain robust and statistically meaningful across a range of alternative bandwidths.

²²For example, Lehne et al. (2018) using data from a rural road construction road program in India find that share of contractors who names matches 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).

²³A growing body of work have used social audits reports to examine leakages between the actual expenditure incurred and the reported expenditure not only in MGNREGA but 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 other channels.

Table 7: Effect of Electing Criminal Politicians on MGNREGA Material Ratio

	(1)	(2)	(3)	(4)
	Material Expenditure Ratio less 40%			
Criminal	-0.072*** (0.019)	-0.050*** (0.016)	-0.051*** (0.014)	-0.047* (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. The outcomes measured is 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These findings seems to indicate that criminal politicians are strategically providing targeted benefits to their constituents rather than engaging in corrupt practices. They are two main explanations supporting this hypothesis: First, following the standard models of distributive politics literature, criminal politicians should concentrate their efforts on distributing more jobs if they are driven by electoral motives (Stokes et al., 2013). In fact, we should expect that voters would have little interest on 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 sizeable reduction in missing labour expenditure but there was no effect on the material component. These findings were attributed to the fact that either the villagers found it easier to detect missing wages or they simply were more concerned with their private interest. This is especially relevant in the context of MGNREGA, since the program self-selects poor households, we can easily construe that voters would 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 as a cheap vote-buying tool for politicians. Second, the expenditure rule creates a trade-off between material and wage expenditure. This means that MLA has to choose between distributing more jobs or spending more on materials. The findings in this paper indicate the criminal politicians seem to prefer the latter.

7.5 Alternative Explanations

In the preceding sections, the results seem to indicate that criminal politicians strategically distribute resources. Although I find that the election of a criminal politician leads to substantial negative effects on local infrastructure growth, they are better at providing work opportunities to their constituents. There two plausible alternative explanations which could partly be driving these results. In particular, I explore if any differences in the availability of funds or demand for work that could be contributing to the baseline findings.

In the first specification, I test if there is any differences in the material expenditure incurred between criminal and clean constituencies. They are two reasons why differentials in material expenses can provide an explanation for the findings: first, 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. Second, constituencies that elect a criminal politician might be undertaking certain type of projects which are more capital-intensive and hence incur higher expenses on materials. Since these projects tend to be more time-consuming, this could perhaps explain the negative difference in the number of projects completed rather the criminal politician being inefficient. Table C.1 provides no support for this argument. If this was the case, we would observe significantly lower allocation of the material component when comparing between criminal and clean constituencies.

A second explanation which could be contributing to the positive effect in

the number of Work Days generated in constituencies where a criminal politician won in close elections could be due to 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 workers to migrate to these areas. This could potentially explain why constituencies that elect a criminal politician observe a rise in the number of work days provided in comparison to clean constituencies. One way to test for this is to look at the number of job cards issued under the program.²⁴ Each individual worker has to apply for a new job card when they move to a new *Gram Panchayat* indicating their willingness to be employed under the scheme. Thus, if workers were moving to constituencies that elect a criminal politician, we should observe a positive difference when comparing between criminal and clean constituencies. 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 constituencies where a criminal politician barely won to ones where they barely lost. This results seem to suggest that the employment demand was relatively similar across the treatment and controls groups. Overall, this put together with the findings provided in Table C.1 provides some assurance that the results do not seem to be driven by differences in material expenditure or worker migration.

7.6 Robustness

7.6.1 Alternative Definitions of Crime

As mentioned earlier, there are several reasons to investigate alternative definitions of criminality, especially in the case of 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

²⁴Ideally, 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).

clean candidate has no charges (and a runner-up who has at least one serious charges). The results of this exercise are presented in Table C.3 and the estimates consistent with the baseline findings: constituencies that elect criminal politicians with serious charges observe a drop in the number of Projects Completed and a rise in the Work Days when compared to constituencies that elect politicians with no serious allegations. Additionally, as we would expect the magnitude of the coefficients are larger in comparison to that of main results implying that the election of serious criminals have potentially higher costs.

Likewise, in Table C.4, I define a politician a criminal if they face corruption charges against them. Again, the results are consistent and show that in constituency where a corrupt politician barely wins exhibits a lower project completion rate but has a higher work allocation in comparison to constituencies where corrupt politician barely lost. Overall, these results put together suggest that the main findings are robust to these alternative definitions of crime thus making it more likely that criminal charges against the candidates true.²⁵

7.6.2 Timing of RD Effect

Until now, the MGNREGA outcomes included the full time period of the MLA term between 2011 to 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 suggest that the results remain qualitatively similar and robust.

Another concern is that there might be high level of volatility in the MGNREGA outcomes annually. Thus, I consider two alternative measurements to test if there is any variation in MGNREGA outcomes over time: first, I estimate the

²⁵RD 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 wins were less likely to be 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 estimates provided in Table A.10. However, the coefficients increase in magnitude and suggest that corrupt politicians have higher treatment effects in comparison to the baseline estimates.

effect of electing a criminal politicians separately for each year of their term. Figure C.1 presents the results of this exercise with the graphical illustration of the RD effect. Looking first at Works Completed in panel (a), the estimates show that the effect is not instantaneous and increases over time. In the first year of being elected, the coefficient is not statistically significant. In the second and third year the coefficient is statistically significant and of a similar magnitude to the baseline results. 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, the figure for Work Days in panel (b) shows that the positive effect 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.

In the last specification, 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.7 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, for Work Days, the coefficient is statistically significant and close in terms of magnitude to the main results for the main bandwidth and double the bandwidth. However, the coefficient loses statistical power at lower bandwidth levels.

7.6.3 Addressing Extreme Values

In this sub-section, 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. It could be that certain regions are more densely populated or have higher state capacity which might explain the differences in MGNREGA outcomes across regions. While these issues should not be directly correlated with the effects of electing a criminal politician, I address this by dropping the five largest values from the sample. Table C.8 provides the estimates for both the outcomes and albeit the effect is slightly smaller, they still remain statistically significant and meaningful.

Another issue is the presence of zeros in certain village clusters. This could be driven by several factors. First, certain regions might take up projects which take longer than one time period to complete. Second, regions with scarcer inhabitation might have a lower requirement for local infrastructure or demand for work. I address this issues in Table C.9 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 put together suggest that the findings are robust to any extreme values in the sample.

7.6.4 Sensitivity of RD Specification

In this sub-section, 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 although leads to a similar estimates as the baseline results and is statically significant, the confidence interval is relatively large. While increasing the bandwidth to larger values the estimates seems to be mostly stable. Likewise for Work Days in panel (b), the point estimates are statically significant and similar to the baseline estimates at higher bandwidth levels. However reducing the bandwidth, the estimates loose statistical power.

In the next specification, I estimate the treatment effects by varying the functional form. Table C.10-C.11 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 to the baseline estimates. Although at high order polynomials or smaller bandwidths, the estimates for Work Days is no longer statistically significant.

The last robustness check, I conduct is to add various covariates in the model. The results of this exercise is 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 the 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 the main findings.

8 Conclusion

In this paper, I estimate the *causal* effects of electing criminal politicians on India's largest anti-poverty program MGNREGA. I find that the election of criminal politician leads to a significant reduction in the number of projects completed under the scheme. In contrast, criminal politicians distribute more jobs to their constituents during their time in office. I additionally estimate for various mechanisms that could be driving these results. In particular, I test if there are any differences in expenditure allocation or leakages in the program and find no conclusive evidence that these factors contribute to the findings. These results remain consistent across a broad range of alternative specifications and robustness checks.

These results are of relevance for several reasons. First, I find that criminal politicians have strong negative effects on generating assets in the constituency that they are elected in. Since investment in local infrastructure is often seen as barometer for development, the results suggest that criminal politicians can have long-lasting impact on economic growth. In this respect, these results are consistent with the literature before that finds that criminal politicians reduce overall economic welfare (Chemin, 2012; Prakash et al., 2019). In contrast, the results provide the first statistical evidence in support of the theory that criminal politicians have the ability to "get things done" (Vaishnav, 2017). I find that criminal politicians seem to strategically offer targeted benefits in terms of higher work allocation to their constituents. In short, the findings in this paper provide a link between these two main competing branches of literature.

Lastly, the findings partly provide an explanation for the recent rise of criminal politicians in the Indian legislature. I find that criminal politicians systematically distribute certain resources that voters might care more about. This could perhaps explain why voters perceive criminal politicians as being competent and vote for them at the ballot. Although, I am sceptical of making any direct inference since

MGNREGA is one of the many development programs offered by the government. It would be insightful to check if criminal politicians use similar distributive strategies in the provision of other public goods and its potential impact on voter behaviour. I leave this to future work.

References

- Afridi, F., & Iversen, V. (2013). Social audits and MGNREGA delivery: Lessons from Andhra Pradesh. *India Policy Forum*, 10(1), 1-47.
- Afridi, F., Iversen, V., & Sharan, M. R. (2017). Women political leaders, corruption, and learning: Evidence from a large public program in India. *Economic Development and Cultural Change*, 66(1), 1–30.
- Aiyar, Y., & Samji, S. (2009). *Transparency and accountability in NREGA: A case study in Andhra Pradesh*. (Accountability Initiative Working Paper No. 1)
- Alsop, R., Krishna, A., & Sjoblom, D. (2001). Inclusion and local elected governments: The Panchayat Raj system in India. *Social Development Paper*, 37.
- Ares, M., & Hernández, E. (2017). The corrosive effect of corruption on trust in politicians: Evidence from a natural experiment. *Research & Politics*, 4(2), 2053168017714185.
- Arulampalam, W., Dasgupta, S., Dhillon, A., & Dutta, B. (2009). Electoral goals and center-state transfers: A theoretical model and empirical evidence from india. *Journal of Development Economics*, 88(1), 103–119.
- Asher, S., Lunt, T., Matsuura, R., & Novosad, P. (2021). *Development research at high geographic resolution: An analysis of night lights, firms, and poverty in India using the SHRUG open data platform*. (Policy Research Working Paper, No. 9540. World Bank, Washington, DC.)
- Asher, S., & Novosad, P. (2017). Politics and local economic growth: Evidence from India. *American Economic Journal: Applied Economics*, 9(1), 229-273.
- Banerjee, A., Duflo, E., Imbert, C., Mathew, S., & Pande, R. (2020). E-governance, accountability, and leakage in public programs: Experimental

- evidence from a financial management reform in India. *American Economic Journal: Applied Economics*, 12(4), 39–72.
- Banerjee, A., Kumar, S., Pande, R., & Su, F. (2011). *Do informed voters make better choices? Experimental evidence from urban India*. (Unpublished manuscript, Harvard University)
- Banerjee, A., & Pande, R. (2007). *Parochial politics: Ethnic preferences and politician corruption*. (CEPR Discussion Paper No. DP6381)
- Bardhan, P. (1997). Corruption and development: A review of issues. *Journal of Economic Literature*, 35(3), 1320–1346.
- Berenschot, W. (2011a). On the usefulness of goonda's in Indian politics: 'Moneypower' and 'Musclepower' in a Gujarati locality. *South Asia: Journal of South Asian Studies*, 34(2), 255–275.
- Berenschot, W. (2011b). The spatial distribution of riots: Patronage and the instigation of communal violence in Gujarat, India. *World Development*, 39(2), 221–230.
- Besley, T. (2006). *Principled agents? : The political economy of good government*. Oxford University Press.
- Boas, T. C., Hidalgo, F. D., & Melo, M. A. (2019). Norms versus Action: Why Voters Fail to Sanction Malfeasance in Brazil. *American Journal of Political Science*, 63(2), 385-400.
- Bratton, M. (2008). Vote buying and violence in Nigerian election campaigns. *Electoral Studies*, 27(4), 621-623.
- Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust data-driven inference in the regression-discontinuity design. *The Stata Journal*, 14(4), 909–946.
- Caselli, F., & Morelli, M. (2004). Bad politicians. *Journal of Public Economics*, 88(3), 759 - 782.
- Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal*, 18(1), 234-261.
- Cattaneo, M. D., Luke Keele, L., & Titiunik, R. (2023). *Covariate adjustment in regression discontinuity designs* (J. R. Zubizarreta, E. A. Stuart, D. S. Small, & P. R. Rosenbaum, Eds.). Chapman & Hall.
- Chattopadhyay, R., & Duflo, E. (2004). Women as policy makers: Evidence from a randomized policy experiment in India. *Econometrica*, 72(5), 1409–1443.

- Chemin, M. (2012). Welfare effects of criminal politicians: A discontinuity-based approach. *The Journal of Law and Economics*, 55(3), 667-690.
- Das, U., & Maiorano, D. (2019). Post-clientelistic initiatives in a patronage democracy: The distributive politics of India's MGNREGA. *World Development*, 117, 239-252.
- Dasgupta, A. (2016). *Strategically greasing the wheels: The political economy of India's rural employment guarantee*. (International Growth Centre (IGC) Working Paper S-89101-INC-1)
- Dey, S., & Sen, K. (2016). *Is partisan alignment electorally rewarding? Evidence from village council elections in India*. (Effective States and Inclusive Development (ESID) Working Paper 63)
- Easterly, W., & Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The Quarterly Journal of Economics*, 112(4), 1203-1250.
- Ferraz, C., & Finan, F. (2008). Exposing corrupt politicians: The effects of Brazil's publicly released audits on electoral outcomes. *The Quarterly Journal of Economic*, 123(2), 703-745.
- Finan, F., & Ferraz, C. (2011). Electoral accountability and corruption: Evidence from the Audits of Local Governments. *American Economic Review*, 101(4), 1274-1311.
- Gulzar, S., & Pasquale, B. J. (2017). Politicians, bureaucrats, and development: Evidence from India. *American Political Science Review*, 111(1), 162-183.
- Imbens, G. W., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies*, 79(3), 933-959.
- Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2), 615-635.
- Imbert, C., & Papp, J. (2015). Labor market effects of social programs: Evidence from India's employment guarantee. *American Economic Journal: Applied Economics*, 7(2), 233-263.
- Jenkins, R., & Manor, J. (2017). *Politics and the Right to Work: India's National Rural Employment Guarantee Act*. Oxford University Press.
- Kapur, D., & Vaishnav, M. (2013). *Quid pro quo: Builders, politicians, and election finance in India*. (Center for Global Development Working Paper,

276.)

- Khwaja, A. I., & Mian, A. (2005). Do lenders favor politically connected firms? Rent provision in an emerging financial market. *The Quarterly Journal of Economics*, 120(4), 1371-1411.
- Kitschelt, H. (2000). Linkages between citizens and politicians in democratic polities. *Comparative Political Studies*, 33(6-7), 845–879.
- Kitschelt, H., & Wilkinson, S. I. (2007). *Patrons, clients and policies: Patterns of democratic accountability and political competition*. Cambridge University Press.
- Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2), 281-355.
- Lehne, J., Shapiro, J. N., & Eynde, O. V. (2018). Building connections: Political corruption and road construction in India. *Journal of Development Economics*, 131, 62-78.
- Maiorano, D. (2014). The politics of the Mahatma Gandhi National Rural Employment Guarantee Act in Andhra Pradesh. *World Development*, 58, 95-105.
- Manzetti, L., & Wilson, C. J. (2007). Why do corrupt governments maintain public support? *Comparative Political Studies*, 40(8), 949–970.
- Martin, N., & Michelutti, L. (2017). Protection rackets and party machines: Comparative ethnographies of “Mafia Raj” in north India. *Asian Journal of Social Science*, 45(6), 693–723.
- McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2), 698-714.
- Mironov, M., & Zhuravskaya, E. (2016, May). Corruption in procurement and the political Cycle in tunneling: Evidence from financial transactions data. *American Economic Journal: Economic Policy*, 8(2), 287-321.
- Muralidharan, K., Niehaus, P., & Sukhtankar, S. (2016). Building state capacity: Evidence from biometric smartcards in India. *American Economic Review*, 106(10), 2895–2929.
- Nanda, V. K., & Pareek, A. (2016). Do criminal politicians affect firm investment and value? Evidence from a regression discontinuity approach. *Evidence from a Regression Discontinuity Approach*.

- Niehaus, P., & Sukhtankar, S. (2013, 2013). Corruption dynamics: The golden goose effect. *American Economic Journal: Economic Policy*, 5(4), 230-269.
- Olken, B. A. (2007). Monitoring corruption: Evidence from a field experiment in Indonesia. *Journal of Political Economy*, 115(2), 200-249.
- Prakash, N., Rockmore, M., & Uppal, Y. (2019). Do criminally accused politicians affect economic outcomes? Evidence from India. *Journal of Development Economics*, 141(C), 102370.
- Stokes, S. C. (2005). Perverse accountability: A formal model of machine politics with evidence from Argentina. *American Political Science Review*, 99(3), 315-325.
- Stokes, S. C., Dunning, T., Nazareno, M., & Brusco, V. (2013). *Brokers, voters, and clientelism: The puzzle of distributive politics*. Cambridge University Press.
- 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-is-second/article23041918.ece>.
- Vaishnav, M. (2011). *The market for criminality: Money, muscle and elections in India*. (Columbia University Working Paper)
- Vaishnav, M. (2017). *When crime pays: Money and muscle in Indian politics*. Yale University Press.
- Winters, M. S., & Weitz-Shapiro, R. (2013). Lacking information or condoning corruption: When do voters support corrupt politicians? *Comparative Politics*, 45(4), 418-436.
- Witsoe, J. (2012). Everyday corruption and political mediation of the Indian state: An ethnographic exploration of brokers in Bihar. *Economic and Political Weekly*, 47-54.
- Zimmermann, L. (2015). *May there be victory: Government election performance and the world's largest public-works program*. (IZA Discussion Paper, No. 9161)

9 Appendix

A. MNREGA Flow Chart

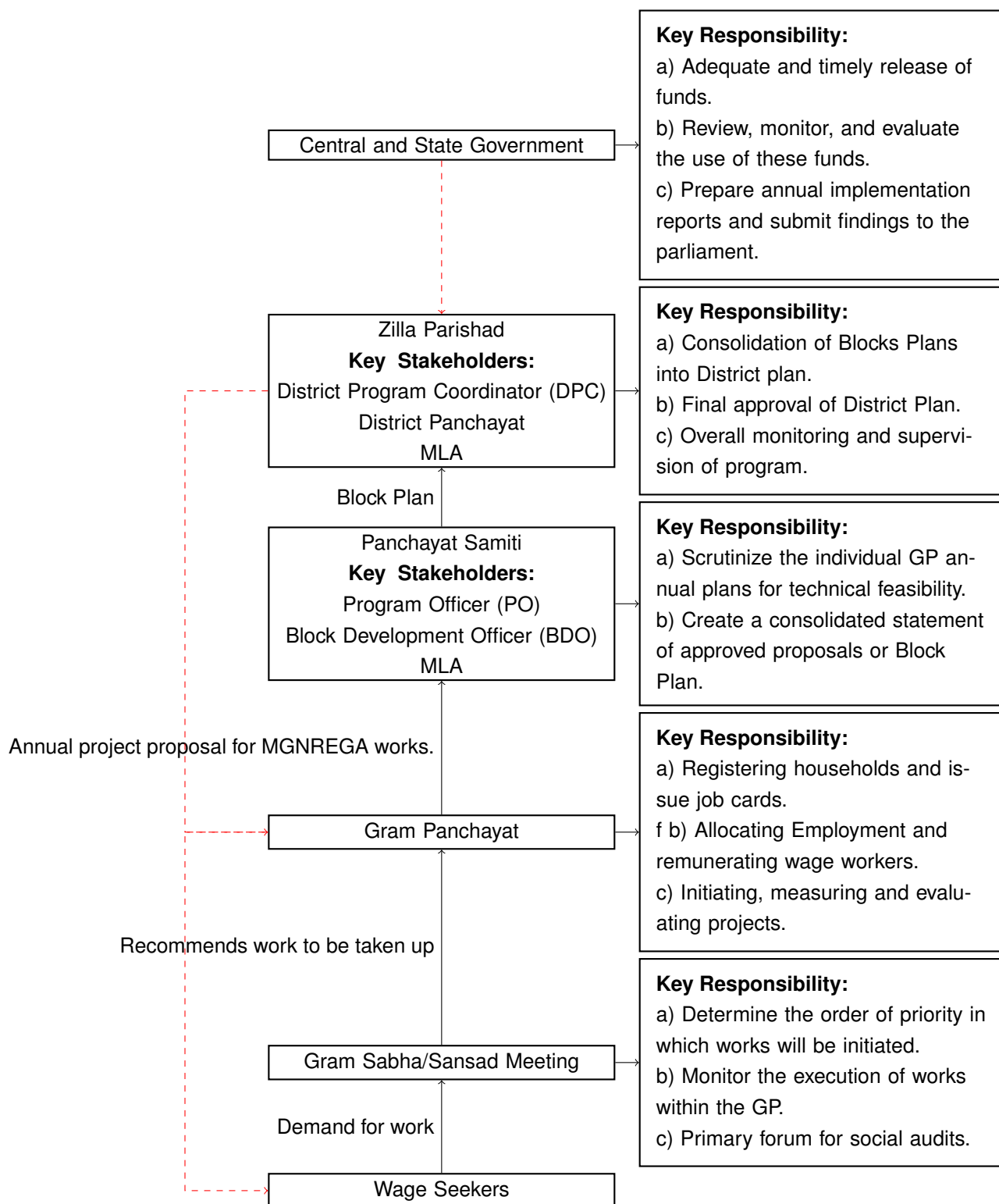
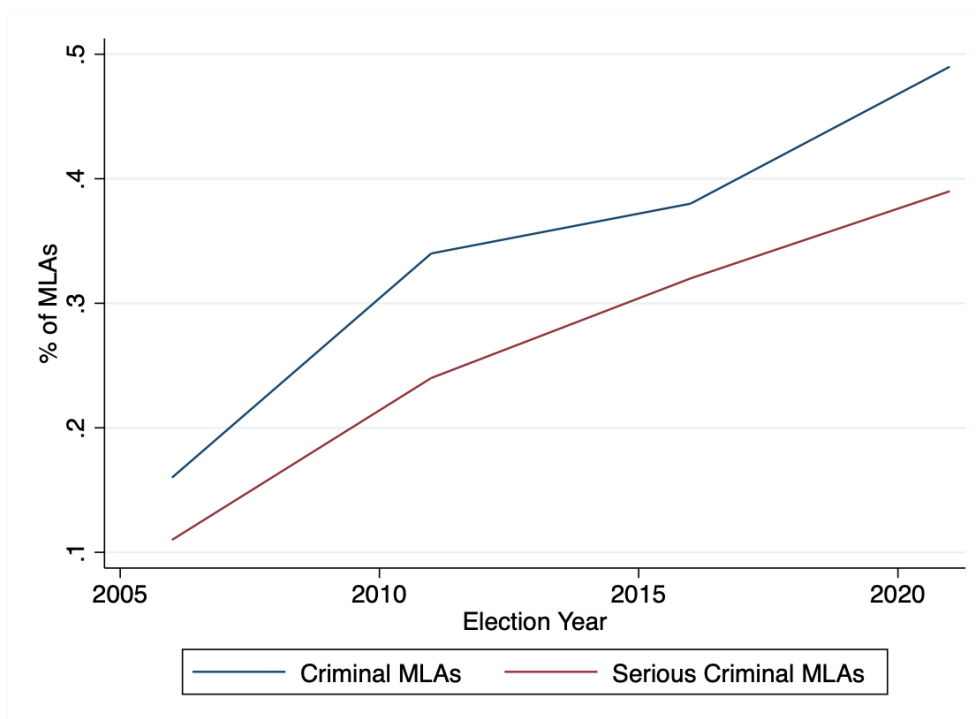


Figure A.1: MGNREGA Functioning

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
<i>N</i>	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 Type 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.

Table B.3: Constituency Profile

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

Table B.4: Candidate Profile

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

C. Robustness Checks

Table C.1: Effect of Electing Criminal Politicians on MGN-REGA Material Expenditure

	(1)	(2)	(3)	(4)
	Material Expenditure/1000 capita			
Criminal	-36,749 (30,786)	-45,442* (27,121)	-11,501 (29,038)	67,834 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Effect of Electing Criminal Politicians on MGN-REGA Work Demand

	(1)	(2)	(3)	(4)
	Job Cards Issued/1000 capita			
Criminal	-36.23 (32.90)	-79.51 (61.65)	-20.35 (20.58)	-64.96 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. 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*** (1.268)	-5.146*** (1.253)	-4.659*** (1.239)	-6.572*** (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*** (491.7)	861.5 (668.6)	835.4** (363.4)	478.3 (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 to 1 if the serious criminal candidate won and equals to 0 if the serious criminal candidate lost. In Panel A the outcome measured is the annual number of projects per 1000 residents. In Panel B the outcome measured is the numbers of Work Days 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. 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** (1.697)	-9.739*** (2.376)	-2.673* (1.484)	-8.687*** (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*** (664.4)	1,240 (885.4)	1,395*** (509.5)	985.2 (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 to 1 if the corrupt candidate won and equals to 0 if corrupt candidate lost. In Panel A the outcome measured is the annual number of projects per 1000 residents. In Panel B the outcome measured is the numbers of Work Days 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. 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*** (1.831)	-10.25*** (2.415)	-1.710 (1.584)	-8.991*** (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*** (646.6)	2,460*** (860.3)	2,159*** (506.9)	1,972** (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			

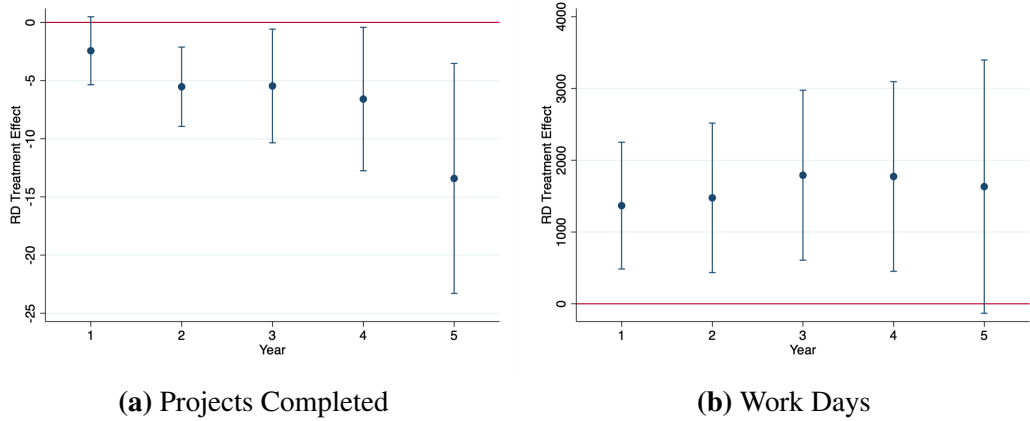
Notes: The dependent variable criminal is a dummy that equals to 1 if the corrupt candidate won and equals to 0 if corrupt candidate lost. In Panel A the outcome measured is the annual number of projects per 1000 residents. In Panel B the outcome measured is the numbers of Work Days per 1000 residents. The model includes 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. 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*** (2.123)	-6.038*** (2.236)	-4.200*** (1.479)	-7.498** (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*** (549.0)	1,417** (568.8)	1,309*** (380.3)	819.8 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. In Panel A the outcome measured is the annual number of projects per 1000 residents. In Panel B the outcome measured is the numbers of Work Days 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. 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



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 numbers of Work Days per 1000 residents. The model includes year fixed effects and the standard errors are clustered at the gp and constituency level. The optimal bandwidth used is a mean squared error optimal bandwidth selector proposed by Calonico et al. (2014). The RD estimates are based on a local linear regression using a triangular kernel.

Table C.7: Effect of Electing Criminal Politicians on MGNREGA for Full Election Period

	(1)	(2)	(3)	(4)
Panel A: Projects Completed/1000 capita				
Criminal	-4.835*** (1.315)	-5.292*** (1.964)	-2.985** (1.219)	-6.372*** (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*** (480.2)	896.8 (603.1)	1,283*** (333.7)	780.4 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. The model includes 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: Addressing Extreme Values (< Top 5 Values)

	(1)	(2)	(3)	(4)
Panel A: Projects Completed/1000 capita				
Criminal	-4.929*** (1.410)	-5.045** (1.971)	-3.377*** (1.177)	-6.766*** (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*** (486.3)	1,263** (514.9)	1,215*** (336.8)	764.2 (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			

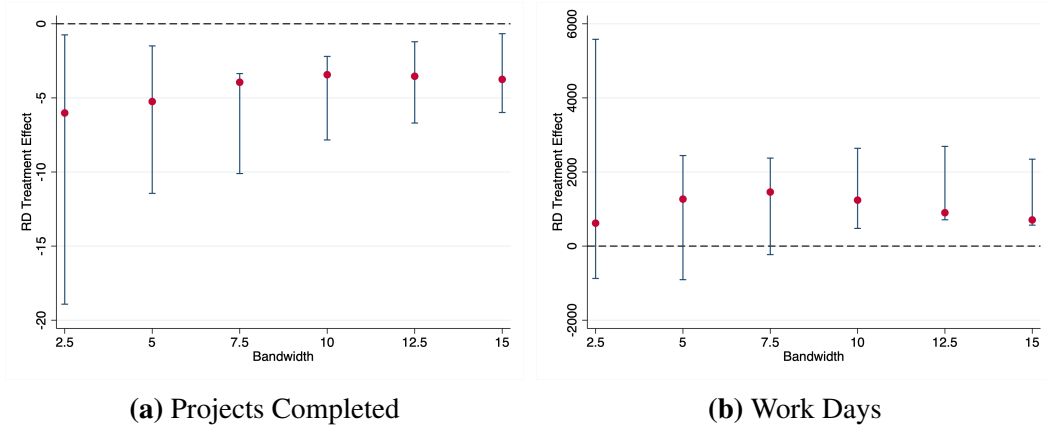
Notes: The dependent variable criminal is a dummy that equals to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. In Panel A the outcome measured is the annual number of Projects Completed per 1000 residents excluding the top 5 extreme values. In Panel B the outcome measured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

Table C.9: Addressing Extreme Values (Excluding Zeros)

	(1)	(2)	(3)	(4)
Panel A: Projects Completed/1000 capita				
Criminal	-5.101*** (1.341)	-5.502*** (1.970)	-3.768*** (1.165)	-5.354** (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*** (486.3)	1,335*** (514.9)	1,028*** (336.8)	950.5 (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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 numbers of Work Days per 1000 residents excluding zeros. 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. Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.2: RD Estimates for Different Bandwidths



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 numbers of Work Days per 1000 residents. The model includes year fixed effects and the standard errors are clustered at the gp and constituency level. The optimal bandwidth used is a mean squared error optimal bandwidth selector proposed by Calonico et al. (2014). The RD estimates are based on a local linear regression using a triangular kernel.

Table C.10: RD Estimates with Different Functional Forms

	(1)	(2)	(3)	(4)
	Projects Completed/1000 capita			
Linear	-5.264*** (1.313)	-5.504*** (1.879)	-3.436*** (1.205)	-6.440*** (2.138)
Quadratic	-6.494** (2.555)	-7.961** (3.487)	-5.153*** (1.439)	-9.754** (4.880)
Cubic	-10.51** (4.143)	-13.43** (6.472)	-7.604*** (2.326)	-6.322 (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 to 1 if a criminal candidate won and equals to 0 if the criminal candidate lost. 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. The model includes year fixed effects and the standard errors are clustered at the gp and constituency level and given in parentheses. The optimal bandwidth used is 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.11: RD Estimates with Different Functional Forms

	(1)	(2)	(3)	(4)
	Work Days /1000 capita			
Linear	1,295*** (477.3)	1,309*** (470.6)	1,147*** (333.4)	746.2 (765.4)
Quadratic	837.1 (814.0)	828.8 (800.8)	1,644*** (538.2)	2,134 (1,608)
Cubic	1,503 (1,419)	1,448 (1,354)	898.1 (750.9)	11,150*** (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 equals to 1 if a criminal candidate won and equals to 0 if the criminal candidate lost. The outcome measured is the annual number Work Days per 1000 residents. The model includes 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 used is a mean squared error optimal bandwidth selector proposed by Calonico et al. (2014). Asterisks denotes the significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

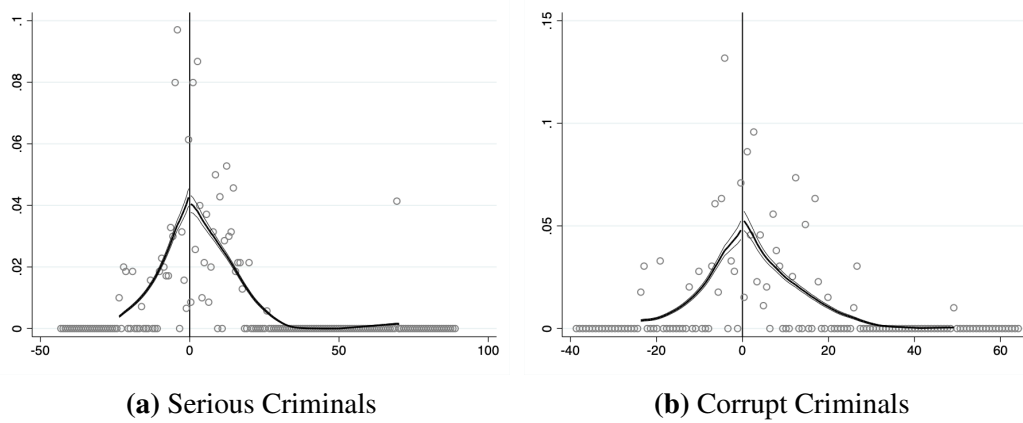
Table C.12: RD Specification with Covariates

	(1)	(2)	(3)
Panel A: Projects Completed/1000 capita			
Criminal	-3.500*** (1.231)	-5.264*** (1.313)	-3.500*** (1.231)
Observations	4359	2459	2459
Bandwidth Size	9.020	4.916	9.020
Panel B: Work Days/1000 capita			
Criminal	1,297*** (430.2)	1,295*** (477.3)	1,297*** (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 to 1 if the criminal candidate won and equals to 0 if the criminal candidate lost. 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. The model includes 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 used is 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



The forcing variable is the margin of a victory that is the difference between 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 clean runner-up. Negative values indicate the difference between the vote share received by a clean winner less that of criminal runner-up. In panel (a) a criminal equals to 1 if they face serious allegations against them and 0 otherwise. In panel (b) a criminal equals to 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	Ruling Party	SC/ST Reserved	Log Total Votes	Voter Turnout	Log Electoral Size
Criminal	0.083 (0.364)	-0.422 (0.275)	0.017 (0.056)	-2.446 (2.053)	-0.011 (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 to 1 if the serious criminal candidate won and equals to 0 if the serious criminal candidate lost. 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 used is 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)

VARIABLES	(1) Log Income	(2) Log Liabilities	(3) Age	(4) Gender	(5) High School Degree	(6) Incumbent	(7) National Party
Panel A: Winner							
Criminal	-0.341 (0.867)	0.893 (3.724)	-3.665 (4.863)	0.108 (0.072)	-0.044 (0.250)	-0.041 (0.089)	0.011 (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 (0.768)	0.169 (3.676)	0.160 (5.491)	-0.183 (0.159)	0.180 (0.141)	-0.015 (0.260)	0.011 (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 to 1 if the serious criminal candidate won and equals to 0 if the serious criminal candidate lost. 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 used is 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)

VARIABLES	(1) Ruling Party	(2) SC/ST Reserved	(3) Log Total Votes	(4) Voter Turnout	(5) Log Electoral Size
Criminal	-0.066 (0.347)	-0.649** (0.324)	-0.016 (0.072)	-2.750* (1.498)	-0.063 (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 to 1 if the corrupt criminal candidate won that and equals to 1 if the corrupt criminal candidate lost. 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 used is 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)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log Income	Log Liabilities	Age	Gender	High School Degree	Incumbent	National Party
Panel A: Winner							
Criminal	-0.374 (0.784)	-0.654 (5.882)	-8.250 (5.350)	0.023 (0.031)	-0.044 (0.250)	0.130 (0.136)	-0.01 (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 (1.085)	-2.336 (4.621)	4.599 (6.398)	-0.290 (0.204)	0.043 (0.284)	0.262 (0.348)	-0.010 (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 to 1 if the corrupt criminal candidate won that and equals to 0 if the corrupt criminal candidate lost. 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 used is 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

SI.No..... 22/16

भारतीय गैर न्यायिक
बीस रुपये
रु.20
भारत
INDIA
RS.20
TWENTY
RUPEES
INDIA NON JUDICIAL

পশ্চিমবঙ্গ পশ্চিম বঙ্গাল WEST BENGAL 20AA 138033

AFFIDAVIT TO BE FILED BY THE CANDIDATE ALONG WITH
NOMINATION PAPER
BEFORE THE RETURNING 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 :



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 :	<p>Ltd ACJM : Asansol :-</p> <p>1) Asansol (south) PS: 164/2006 (GR 840/2006)</p> <p>2) Asansol (South) PS: 276/95</p> <p>3) Hirapur Ps : 158/2009 dt 19/01/2009</p> <p>4) Asansol (South) PS: GR 1599/96;321/96</p> <p>Ltd SDJM Asansol: -</p> <p>1)Asansol (south): 9/93 (GR 43/93)</p> <p>2) Asansol GRPS :-65/90 dt 28/05/1990</p> <p>Ltd. ACJM In-charge:-</p> <p>1) NGR 816/2014 Asansol PS: GDE 1293/2014 dt 21/04/2014 under 32 Police Act.</p>
(b)	The details of cases where the court has taken cognizance. Sections of the Act and description of the offence for which cognizance taken:	<p>1) Asansol-6RPS cases No 65/90: U/S: 147/332/427/342 IPC—9MPO Act;108IR Act</p> <p>2) Asansol (south) PS-276/95 : U/S 148/149/323/516 IPC</p> <p>3) Asansol(south)-164/2006; U/S 143/447/427/186/353/ GR-840/2006</p> <p>4) Asansol (South)- 09/93;u/s147/148/149/353/323/427/435 IPCV</p> <p>5) Hirapur PS—158/2009; u/s 143/342/352/86/353 IPC</p> <p>6) NGR 816/2004; GDE No.- 1293/2014</p> <p>7) Asansol (south) PS: 321/96 u/s 143/448/427/506 : 3/4 T P Act</p>
(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 Asansol Dakshin constituency in the West Bengal 2016 state assembly elections. The full version of the affidavit is available on the ECI website.