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Political Favoritism by Powerful Politicians: Evidence from Chief Ministers in India*

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Abstract

We study whether in single-member-district legislative systems, powerful politicians engage in political favoritism towards their constituents. The focus is on the chief ministers of Indian state governments. Using night light intensity as a measure of economic activity, we find that a constituency represented by a sitting chief minister exhibits about 13 percentage increase in luminosity relative to all other constituencies. The effect comes predominantly from the cases where the chief minister's constituency lies outside their birth region. Neighboring constituencies, particularly those with strategic political value, also benefit from this windfall, suggesting the mechanism at play is likely to be political expediency rather than in-group favoritism.

Keywords: *Distributive Politics, Ethnic Favoritism, Rent-seeking*
JEL Codes: D72; R11

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1 Introduction

There is enduring interest among political economists in understanding why some districts or constituencies succeed in receiving a disproportionate amount of distributive benefits. Several explanations have been offered. Golden and Min (2013) summarize 150 studies from around the world classifying them by different hypotheses about the nature of distributive politics. These range from the instrumentalist—i.e., politicians target benefits to those voters whose support is crucial to winning the election, to the rent seeking—i.e., politicians treat distributive benefits as rents to be expropriated for themselves, or their extended selves such as their family, clan or ethnic group.[1]

In a recent study, Hodler and Raschky (2014) provide a detailed cross-country analysis using the birth district of the head of the national government as a proxy for his/her ethnic base. They show that these districts enjoy considerable economic gains compared to other areas. In particular, the estimated effect capturing such rent seeking behavior by powerful politicians is particularly salient in states where democracy is weak or absent. Similarly, using the example of governors of Russian state, Tkachenko and Esaulov (2020) show that in polities with weak institutions, sub-national rulers have considerable discretion in directing/extracting resources. They find that governors who do not have pre-governing local ties in the region demonstrate greater predatory behavior, compared to governors with local ties (insiders). The measure of such predatory behavior is the inefficiency and favoritism in contract allocation for public projects.

A natural question then arises: can democratic institutions help mitigate such distortionary policies through electoral and political incentives? On the other hand, even in democracies, political power enjoyed by the heads of government gives them considerable influence over a vast array of policy instruments, which can in turn be also targeted towards recipients of their choice. This target may be their own constituency, say, for reasons of ethnic affinity if the constituency represented by the politician has a greater concentration of co-ethnics. Or, it could be due to strong (re)electoral concerns, for instance, when the leader's constituency is viewed as a 'prestige seat', winning it with a handsome margin may be crucial to retaining the position as head of the ruling party.[2] At the same time, to be

[1]Examples of rent seeking as ethnic favoritism by politicians include Kramon and Posner (2013), Franck and Rainer (2012), Kasara (2007), Burgess et al. (2015). Examples of distributive politics for instrumentalist reasons are rather numerous; for signal examples see Dixit and Londregan (1996), Stokes (2005) and Stokes et al. (2011).

[2]Such prestige seats are a salient feature, particularly in our setting of India. Political parties and individual leaders have long associated themselves with specific constituencies in both Federal and State legislatures in India. One recent prominent example is the 'embarrassment' caused by the loss of the constituency of Amethi by the President of the Indian National Congress (INC), Rahul Gandhi, in the recently concluded Indian General Elections of 2019, a seat that was held by the INC for almost 52 years.

chosen the leader of the legislative majority, politicians in leadership positions must also win support of other legislators who might represent different interests, compelling them to target benefits to their constituencies, especially if their own reelection prospects are secure. Halse (2016) is a good example of the standard political incentives encountered by a legislator in deciding local public investments. The author finds evidence for the idea that each representative has an incentive to choose projects which concentrate benefits locally but whose costs are spread-out over all districts.

In order to explore these issues, we focus on the world's largest democracy, India. In particular, we focus our attention on Indian state governments and examine the extent of distributive benefits channeled by state government heads towards their electoral constituencies. Our approach has the advantage of holding constant the political and electoral milieu. Furthermore, studying a parliamentary democratic system allows us to shed light on whether constituencies with some non-electoral affinity to the politician, like ethnicity or regional affiliation, tend to gain more or whether such windfalls are more likely to be driven by electoral incentives. The head of the state government, referred to as the Chief Minister (CM), is analogous to the prime minister in the central government, and as such enjoys wide discretionary powers over important decisions at the state level.

We employ a difference-in-differences methodology where the treated units comprise all constituencies whose elected member of legislative assembly (MLA) becomes the CM of the respective State in that electoral cycle. All other constituencies act as the control units.[3] As our measure of local economic activity we use satellite data on night light activity, which we then map to our spatial unit of analysis: an assembly constituency. Our results show close to a 13 percentage increase in night light activity in the CM's constituency relative to all other constituencies. Furthermore, we find no evidence of differential trends before treatment, i.e. 'treated' constituencies do not appear to be undergoing increased activity prior to their elected members becoming chief ministers of their respective state.

We unpack this baseline finding by studying the heterogeneity of the effects by the affinity of the CM to their electoral constituency. Following Hodler and Raschky (2014), we proxy ethnic affinity by whether the CM's constituency lies in their region of birth as well. Politicians contesting from their birth districts will likely have more constituents with whom they share ethnic affinity (kinship/clan/caste/sub-caste). Ethnic affinity with their voters can lead to politicians being able to engage in rent seeking behavior without having to face penalty at the polling booth. For instance, Kauder and Potrafke (2015) document the case of SCU (Christian Social Union) politicians in Bavaria who engaged in nepotism in public em-

[3]We conduct robustness checks by restricting the set of control constituencies to those which only belong to opposition parties in a given electoral cycle as well.

ployment and yet did not suffer lower re-election prospects. If ethnic altruism like concerns are strong then one might expect higher benefits channeled towards these constituencies. On the other hand, politicians are more likely to be guaranteed a higher vote share even without channeling distributive benefits to their constituents if voting takes place along ethnic lines. This is particularly salient in our setting given that ethnic affinity has been shown to play an important role in voters' support of politicians in India (see, for instance, Anderson et al. 2015; Banerjee and Pande 2007). Contrary to the findings in Hodler and Raschky (2014), we find that the estimated treatment effect is concentrated almost entirely in those constituencies that do *not* lie in the birth district of the CM.[4] This suggests that when a CM does not share ethnic affinity with his constituents (a 'non birth CM'), he has to work harder to win their support in seeking his reelection relative to a 'birth CM'. This compels him to transfer more distributive benefits to his constituency relative to the birth CMs.

We explore heterogeneity in our findings along a number of dimensions. The estimated effects are stronger for the CMs of more corrupt States and for constituencies that are primarily rural. This result, while in line with Hodler and Raschky (2014)'s finding that weak polities exhibit greater *regional* favoritism, need not emanate from *ethnic* favoritism, as we discussed above. We also explore the dynamics in our baseline effects. Although the CM constituencies are developing similar to other constituencies three years prior to treatment, there is a sharp increase in night light activity in the first three years of the chief minister's tenure, which then dissipates toward the end of the term and goes back to zero post-tenure signifying that there are no long term gains in regional development for CM constituencies.

We conduct a similar analysis for the constituency of the opposition leader in the State assembly as well and uncover weak evidence for some form of predatory politics in operation. The constituency that the leader of the main opposition party belongs to seems to fare worse compared to all other non-CM constituencies.

We also explore regional spillovers and document increases in night light intensity at a very local level, largely restricted to the immediate neighbors of the CM constituency. This analysis also provides suggestive evidence of a strategic element in operation in vein of the instrumentalist nature of distributive politics. Among neighboring constituencies, CMs seem to only invest differential funds in those state assembly constituencies that fall in the same Lok Sabha (LS) or federal constituency that the CM's own constituency lies in. India, much like other established democracies, has 'upward' mobility of politicians with individuals starting from the lower level of government and progressing all the way to the federal level,

[4] There are a number of key differences between our setup and the one in Hodler and Raschky (2014), which we outline later in this section.

and LS constituency that contains the CM's local constituency would be the obvious choice of the constituency for the CM to contest for higher office from.[5] The patterns of results we find in our spillover analysis is consistent with this hypothesis.

Finally, we undertake a robustness exercise for the parallel trends assumption crucial in difference-in-differences setup. We employ the interactive fixed effects (IFE) framework of Bai (2009), which allows us to relax this assumption by allowing for differential trends in a more flexible way using factor methods. For instance, if there is a federal development program from which constituencies can benefit in heterogeneous ways then such unobservable trends can potentially complicate inference in a standard difference-in-differences setting. The IFE framework helps control for precisely such dynamics. Our baseline analysis passes this check giving credence to the idea that chief ministers are indeed differentially developing their electoral constituencies and unobservable time varying confounders are unlikely to be biasing our estimates.

Our paper contributes to the growing empirical literature looking at political favoritism in the provision of government services and its effect on economic outcomes in different regions and/or institutional contexts. In the context of a representative democracy, the literature looks at the effect of both the incentives as well as ability/power of an electoral district's representative on the share of distributive benefits that a district receives.[6] For instance, Aidt and Shvets (2012) show that legislators facing term limits tend to bring less distributive benefits to their constituents, indicating the role of re-election incentives. Regarding the role of the politician ability, it has been hypothesized, in the context of US Congressional politics, that districts and states represented by more senior politicians or those sitting on influential committees, receive a favorable treatment in delivery of public goods and in location of federally sanctioned projects. For instance, Levitt and Poterba (1999) find that States represented by more senior Congressional members exhibit a higher growth rate, which they treat as an overall measure of favorable policies towards these states.[7] Kramon and Posner (2013) point out that there is a great deal of variation in the incidence of political favoritism in terms of the means used, and to whom the benefits accrue. Several studies, primarily

[5] A shining example of this mobility is the current prime minister of India, Narendra Modi, who started as a regional worker of the Rashtriya Swayamsevak Sangh (RSS) and then became the chief minister of Gujarat in 2001, and eventually got elected as the prime minister in 2014. For an analysis of various career trajectories of politicians in different multi-level democratic systems, see Borchert (2009).

[6] A commonly used term for such benefits, particularly in the U.S. context, is pork-barrel spending. The idea that re-electoral concerns are an important motivation for legislators wanting to channel pork-barrel spending to their districts is well understood. However, this term typically has a negative connotation as being wasteful. Distributive benefits is a more generic term and does not have an adverse connotation.

[7] Other examples include Knight (2005) and Knight (2008) which look at the value of being a proposer as well as the bargaining power of legislators more generally in legislative bargaining settings, and Larcinese et al. (2006) and Berry et al. (2010) which look at the distributive powers of Presidents.

focusing on African countries, have documented instances of ethnic favoritism in specific government policies such as agricultural taxes (Kasara, 2007), health and education (Franck and Rainer, 2012), and road construction (Burgess et al., 2015). Brollo and Nannicini (2012) document favorable treatment received by state-aligned municipalities in Brazil.

In the context of India, Asher and Novosad (2017) show that constituencies represented by representatives belonging to the ruling party receive favorable treatment than those belonging to the opposition. In an interesting paper, Fiva and Halse (2016) show that hometown/land bias is not limited to systems with single member districts, but also occurs in closed list proportional representation systems. While the majority of literature on distributive politics suggests regional/ethnic (often both) favoritism, Fisman et al. (2020), in the case of membership to China's politburo, find evidence of regional/ethnic penalty, i.e., those with college or hometown affiliation with the Politburo members have a 5-9 percentage points lower selection probability. However, the channels of regional favoritism, or a lack thereof, that we are interested in exploring are primarily in the context of democratic systems.

De Luca et al. (2018) extend the framework of Hodler and Raschky (2014), and using data from 140 countries show that the top political leader in a country, for instance the prime minister or president, tend to favor their ethnic homelands in terms of development as measured by night-light activity. However, there are some key differences between those two studies and our analysis here. First, both these papers analyze the existence of potential favoritism shown only by the head of the federal government across a large sample of countries with different political regimes. In contrast, our study focuses at the heads of state governments and sub-national electoral districts and thus studies a similar phenomenon at a much finer level. For instance, our unit of analysis is much smaller in size, about 1/10th in area of the administrative district used in the above studies, and hence we can locate more precisely the recipients of the leaders' favors. This in turn also allows us to uncover important patterns in the spatial spread of political favoritism in and around the home constituency of the chief minister. Second, in our setup the political leader has to be an elected member of their state's local assembly, which makes our work closer to the literature on distributive politics. Nevertheless, a major motivation of the analysis below is to study how ethnic and regional affiliations of elected official might also shape the nature of distributive politics. In this sense, we are combining the above two approaches to studying political/regional favoritism exhibited on part of powerful politicians.

The rest of this paper is organized as follows. Section 2 gives a brief institutional background of the Indian political system. Section 3 gives details on the data that we employ in our study, followed by section 4 that outlines our empirical methodology. Section 5 presents the results and Section 6 concludes.

2 Institutional Context

India has a federal system of government with 29 states and 7 union territories. Each state has a legislature, typically referred to as state/legislative assembly, in which legislators are elected from Local Assembly Constituencies (LACs). The Chief Minister (CM) is the head of the state government, analogous to the prime minister in the central government. State assembly elections are held every five years, but not synchronously with the central elections. There are no term limits for the chief minister.

The Constitution of India provides three lists—State List, Union List, and Concurrent List—which specify the areas that come under the state, central, and joint jurisdiction, respectively. Prominently, the states have the responsibility for making laws, and control the expenditure on items such as police, public health, agriculture, roads, local markets, industrial policy (except for nationally sensitive sectors). Additionally, items such as education and electricity provision also come under State jurisdiction on account of them being on the Concurrent List.

As leader of the ruling majority in the assembly as well as the council of ministers, chief minister is a powerful position in state politics in India. The powers enjoyed by the chief minister arguably give him/her a say in decisions that have distributive consequences over different constituencies that goes well beyond the discretionary funds meant for local area development which are available to all members of the State Assembly (see Asher and Novosad, 2017). It therefore stands to reason that a chief minister would try to use his discretionary powers to either benefit his own constituency and/or the constituencies held by his party members and/or try to divert resources away from those constituencies held by the opposition. The exact nature of such behavior depends on the incentives faced by the chief minister.

There is substantial anecdotal evidence alluding to the existence of such favoritism on the part of chief ministers in India. For example, the constituency of Gorakhpur, from which the newly appointed Chief Minister of Uttar Pradesh (UP), Yogi Adityanath, was elected, received "VIP treatment thanks to a host of allocations in the UP Budget" (Times of India, 2018). The projects included a specialty medical department for the city's medical college, a new 110 kilometer express-way, an auditorium and a new zoo. Similarly, while reporting the budget allocation in the newly formed state of Telangana, the Deccan Chronicle stated, "For those interested in knowing the flagship programmes of the TRS government, there is no need to go around the state. A visit to Chief Minister K. Chandrasekhar Rao's home constituency of Gajwel, is enough to see them all." (Acharyulu, 2018).

It is not only the chief ministerial constituencies that may receive a favorable treatment.

Important allies and politically valuable constituencies may also be chosen for that purpose. In 2012 the constituency of Chevella in Andhra Pradesh received a '60 million dollars bounty' in terms of various infrastructure projects justified on the basis of long standing political links between the political party of the chief minister and the constituency (Ifthekhar, 2012). On the other hand, there are also claims, mostly by opposition members, suggesting that certain constituencies, particularly those held by opposition party leaders are neglected or that projects previously assigned to them are scrapped or diverted.[8]

While anecdotal evidence is indicative, a more thorough empirical treatment to establish the existence of such political favoritism is important. For instance, one possibility that can explain away the above evidence is the potential for over reporting by news media for anything related to the chief minister's constituency given their salience. Furthermore, much like any ordinary constituency, every chief ministerial constituency also gets an entitled development fund and hence the crucial question is of differential development compared to other constituencies in the state.

3 Data

We compile information from a number of different sources to construct the dataset used in this study. Following a recent stream of literature studying economic growth, especially in developing countries, we proxy local economic development by night-light activity based on satellite imagery. Henderson et al. (2012) was one of the first papers that employed night light data as a proxy for economic activity. Since then a number of studies have used satellite imagery as a measure of local economic development in diverse settings. We extract night light information from the database maintained by the National Oceanic and Atmospheric Administration (NOAA). These data are collected by U.S. Air Force satellites, and the subsequent raw data is then cleaned to reflect light activity which is primarily a result of man-made processes. The NOAA provides annual data at scales of less than 1 square kilometer from 1992 onward. We use ArcGIS to map these data to the level of the local assembly constituency, our primary geographic unit of observation.[9] Data on electoral characteristics for each local assembly or general assembly constituency comes from the statistical reports compiled by the Election Commission of India. This resource provides information on top two candidates for each constituency, their party affiliations, the margin of victory, and total voter turnout among other measures. Next we hand-collected data on

[8]See for instance Wadhawan (2018) and Dwarakanath (2018).

[9]We create similar data at the Lok Sabha (Federal constituency) and the administrative district level as well, which we employ for various specification checks.

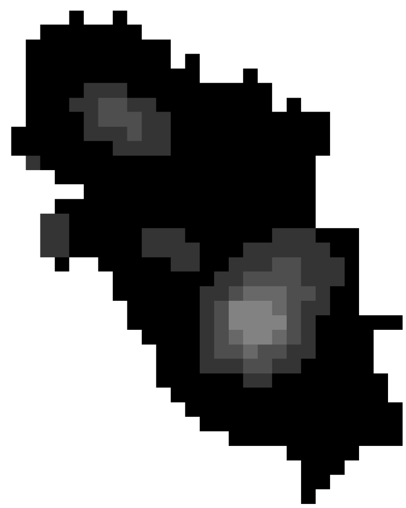
Figure 1: Night Light Activity - Maddur, Karnataka

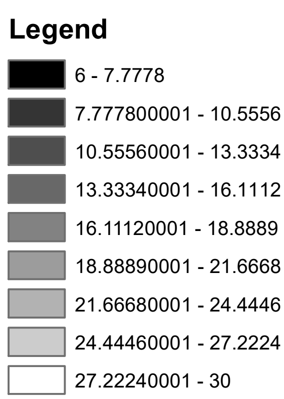
(a) 1997 - 2 years Before Power

(b) 2001 - 2nd Year of Power

(c) 2002 - 3rd year in Power

(d) 2005 - Two Years After Power





all Chief Ministers (CM) across 17 major Indian States for the period 1992 to 2008.[10] We compile information on the CM's birth region, which in our main analysis corresponds to the local assembly constituency that he or she was born in, the exact dates they remained in power, and their party affiliations. We match these with a candidate characteristic database maintained by the Association for Democratic Reforms (ADR), an independent think-tank that was instrumental in the lead up to the eventual Indian Supreme Court judgment that required candidate affidavits to be publicly available. These affidavits contain information on education, asset details, and criminal records for all aspirants of electoral office at both the State and Federal level.

Figure 1 presents night light activity for a representative constituency: Maddur in the state of Karnataka. Maddur's state member of parliament became the chief minister of Karnataka in 2000. Figure 1(a) shows night light activity in Maddur, 2 years before it became a CM constituency. Two years into the term we start seeing a brighter spot in the south east of 1(b). This becomes brighter and radiates out in 1(c), and then the whole constituency darkens again 2 years after the term of the CM ended as depicted in 1(d). In our empirical analysis, we will try to tease out whether this is an actual effect of Maddur being the constituency of the chief minister of Karnataka, and was a recipient of differential resources as a result, or whether this is a result of some pre-existing spurious trend.

4 Empirical Methodology

4.1 Baseline Specifications

The empirical methodology we use is straightforward. We implement a difference-in-differences style framework with specifications of the following format,

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{cst} + \lambda_c + \lambda_{st} + \varepsilon_{cst} \quad (1)$$

Our primary measure of economic activity is captured by $log(Nightlight_{cst})$, which is the log of average night light intensity in local assembly constituency c in state s and in year t.[11] A constituency c is considered to be 'treated' in year $t = \tau$, where τ indexes

[10] Due to the reshaping of electoral boundaries, at both the State and Federal level, we cannot extend our sample period all the way to the present.

[11] Following the literature, we add 0.01 to our dependent variable to deal with observed intensities of zero in our data. In addition to this, as a robustness exercise we also employ the inverse hyperbolic sine transformation, which is immune to the zero observed value concern (Johnson, 1949; Burbidge et al., 1988). Results are very similar across specifications. The night light measure is top-coded, and hence the data has a limitation in measuring extremely brightly lit areas. Due to this concern, we drop the top 1% of observations by night light activity, although our results are robust to their inclusion.

the tenure of the current chief minister of state s and who is elected from c, represented by CM^{τ}_{cst}. We will refer to this constituency as the CM constituency in the subsequent discussion. Constituency specific time-invariant factors are captured by λ_c, which controls for the concern that CM constituencies might be prominent constituencies, historically, and can have higher levels of pre-existing economic development. Similarly, λ_{st} is a state x year fixed effect that flexibly controls for potential shocks that might hit all constituencies in a given state and year. Finally, ε_{cst} is the usual error term. We cluster our standard errors at the constituency level.

Because of the staggered nature of state assembly elections in India, chief ministers can be sworn into office at any time during the year. At the same time due to administrative and implementation delays, one would expect lags in the initiation of developmental projects and observing their impact through changes in night light intensity. For this reason, in our baseline specifications CM^{τ}_{cst} takes the values 1 in year $t = \tau$ only if the chief minister takes charge before June, for the first year of tenure ($\tau = \underline{\tau}$), and is 1 for year $t = \tau$ if the CM leaves office after June for the last year of tenure ($\tau = \bar{\tau}$).[12] For most of our analysis, we also implement a lagged version of our treatment variable, motivated by the above cited concerns.[13]

Under equitable distribution of resources across constituencies within a state, γ should be close to zero and statistically insignificant. A positive estimated coefficient γ will provide evidence for preferential treatment of chief ministers to their own constituencies relative to the rest of the state. However, whether one can interpret this coefficient as causal evidence of political bias is subject to standard pitfalls in a difference-in-differences setup: the potential of pre-existing differential trends across CM and non-CM constituencies spuriously manifesting as a treatment effect. For instance, if prospective candidates for the chief minister position differentially contest from areas that were doing worse then γ would underestimate the true effect. Similarly, in the more likely scenario of future CM constituencies trending positively we would spuriously overestimate the true impact. We, therefore, augment equation (1) with various ways of controlling for pre and post spurious effects, closely following the specifications used in Hodler and Raschky (2014). This gives us estimating equations of the following format,

[12] It takes the value 1 for all intervening years, assigning the relevant constituency to the treatment group for the length of the tenure of the chief minister. We conduct robustness tests by defining treatment without imposing this restriction and the results are very similar to the baseline.

[13] This lagged specification is the primary estimating equation in Hodler and Raschky (2014).

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{cst} + \phi_1 \sum_{k=1}^{3} CM^{\underline{\tau}-k}_{cst} + \phi_2 \sum_{k=1}^{3} CM^{\bar{\tau}+k}_{cst} + \lambda_c + \lambda_{st} + \varepsilon_{cst} \quad (2)$$

Here $CM^{\underline{\tau}-k}_{cst}$ takes the values 1 up to three years prior to constituency c becoming a CM constituency and ϕ_1 captures whether constituency c was already developing differentially even before coming into power. Similarly, ϕ_2 captures the analogous impact up to three years after the tenure of the chief minister ends for constituency c. If ϕ_1 and ϕ_2 are statistically indistinguishable from zero then this would provide further credence to our estimation strategy in uncovering the differential development undertaken by chief ministers in their own constituencies. In section 5.4 we expand on this further and investigate a dynamic treatment effects model, akin to Autor (2003).

4.2 Interactive Fixed Effect Specification

The main assumption in difference-in-differences style methodologies is the so-called common trends assumption. Most researchers are concerned whether it holds or not, and we generally see robustness checks that control for potential differential trends across treatment and control in various ways. For instance, our setup in section 4.1 is also mindful of this and we flexibly control for potential trends both before and after treatment in various ways in equation (1) and (2). However, one concern that can still complicate inference, and that is not captured by the above specifications, is if a common shock hits the entire system and impacts all units in potentially heterogeneous ways. For instance, in our case if a nation wide development program is launched throughout India with different constituencies benefiting in different ways then it can bias the estimated coefficient measuring our treatment effect. Similarly, macroeconomic conditions would impact individual units differentially engenders similar inference related concerns. While state specific year fixed effects will mitigate some of these concerns, we implement a more formal robustness check in the form of Bai's (2009) interactive fixed effect (IFE) models to explore the sensitivity of our estimates to such potential unobservable shocks.[14] These models assume a more flexible error structure and estimate specifications of the following form,

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{ct} + \lambda_c + \lambda_t + \theta_c f_t + \varepsilon_{ct} \quad (3)$$

[14]The literature on panel data with interactive fixed effects has been growing steadily over the past decade. For a theoretical overview of this literature refer to Hsiao (2018). For a more empirically driven summary, especially for difference-in-differences style research designs, refer to Gobillon and Magnac (2016). For an implementation of IFE to an actual empirical problem, refer to Kim and Oka (2014) and Givord et al. (2018).

where we now add a constituency and a year fixed effect, and instead of using time effects interacted with state fixed effects to capture unobservable trends, we use a more flexible factor structure on the error term. Here f_t is an $r \times 1$ vector of unobserved common shocks and θ_c is an $r \times 1$ vector of factor loadings that captures constituency-specific response to the common shocks. All other variables are defined as in equation (1). As Kim and Oka (2014) explain, the common factors have a purely statistical interpretation and correspond to the principal components of the error term or in our case the 'principal' part of night light activity that is not explained by the included controls. This factor structure provides the added flexibility in IFE models in capturing more general forms of unobserved heterogeneity compared to the commonly used approaches, like unit specific linear time trends, that require *a priori* assumptions.

5 Results

5.1 Baseline Results

In this section we present our baseline results. We report findings for both a contemporaneous measure of constituency c being a CM constituency as well as its first lag. Column (1) of Table A.3 presents the estimated effect based on equation (1). We estimate a γ coefficient of 0.1220 ($p < 0.01$), which amounts to a 13 percentage increase in night light intensity for each year a constituency's elected representative in the state assembly is the chief minister of the state.[15] Column (2) then adds controls to detect similar 'impacts' 3 years before and 3 years after the constituency became a CM constituency. The baseline estimate falls only slightly to 12.6 percentage, with neither of the added controls being statistically significantly different zero. In column (3), we further test the potential concern of differential trends across CM and non-CM constituencies by adding a linear trend for 3 years prior and 3 years after the CM tenure.[16] The estimated coefficients are close to zero and statistically insignificant. Column (2) and (3) provide evidence that the difference-in-differences strategy provides an adequate setup to explore the treatment effect of interest.[17] The last three columns of Table A.3 redo the analysis for the lagged measure of CM tenure. We estimate slightly attenuated effects,

[15] The percentage effect is calculated in the standard way using the following formula: $100(e^{\beta} - 1)$.

[16] As a robustness exercise, we add a CM constituency specific linear and quadratic time trends for our entire sample period as well. Results are robust to both additions and presented in appendix Table A.1.

[17] For the analysis in columns (2) and (3), our estimates are not sensitive to the time window chosen to calculate the trends pre and post tenure. We repeat this analysis by varying the window between 4 and 10 years and our estimated coefficient from these specifications remains between 0.110 and 0.119.

as expected, but the specification checks in columns (5) and (6) come through again.[18]

The above findings provide evidence for a prevalent differential effect for a CM constituency, however, determining the underlying mechanism for this phenomenon is much harder. For instance, as outlined earlier, chief ministers could have political expediency motivated concerns where they want to maximize their chances of getting re-elected from the same seat. On the other hand, Hodler and Raschky (2014) provide convincing evidence from a cross-country analysis that political leaders exhibit favoritism toward sub-national regions they have an affinity with. In their analysis, they use the birth region of the leader as a measure of this affinity.

Motivated by this finding, we implement a similar analysis to explore whether the same phenomenon can help explain our findings. We collect information on the birth district of each CM in our sample, and split the treated units into two groups: CM constituencies that lie in the birth district of the CM and those that do not.[19] Table 2 presents the results from this exercise. In the context of India, we document that a constituency that *does not* lie in the birth district of the chief minister witnesses an average increase of over 20 percentage when its elected member is the chief minister. The analogous effect for those constituencies in the actual birth district is under 5 percentage and statistically insignificant. More importantly, as columns (3) and (6) show, these cannot be explained by differential trends or spurious effects around the tenure of the chief minister across birth and non-birth constituencies.[20] Ethnic favoritism as well as political expediency could be at play in determining the extent of favorable treatment received by CM's constituency.. Our results show that in the context of Indian state-level politics, the ethnicity effect is is negligible. This raises the possibility of political expediency as an alternative explanation. We find support for this explanation in the form of significantly higher transfers by non-birth CMs. Additionally, we find greater transfers to those neighboring districts, as discussed in section 5.4, which lie in the federal constituency, indicating the possibility that the local politician may be investing in cultivating voter support for forays into federal politics. This behavior also suggests political expediency at play.

However, a recent finding in the literature suggests that ethnic favoritism is extremely prevalent across the world, with De Luca et al. (2018) terming it as 'an axiom of politics'.[21]

[18] We re-estimate our baseline specification without putting in the restriction of defining first year of tenure conditional on oath taking before June. In other words, we treat all constituencies as treated the year a CM is elected from there. The results are slightly attenuated for the contemporaneous specification, due to contamination bias type concerns as expected, but are almost identical for the first lag specification. Specification checks based on variants of equation (2) also pass.

[19] On average there are around 11 to 12 local assembly constituencies in a given district.

[20] The results presented above are completely robust if we measure night light in per capita terms.

[21] Likewise, Do et al. (2017) document favoritism by powerful bureaucrats towards their clan members.

Their main finding shows that political leaders differentially invest in their birth regions regardless of political expediency related concerns. Although they only focus on the head of the federal government in their analysis, their findings do seem to be at odds with our results in the context of India. One possible explanation for the pattern of political favoritism that we uncover is the practice of voting along ethnic/caste lines. Previous literature has documented this in the context of South Asia in general and India in particular (Anderson, Francois, and Kotwal, 2015). Birth regions of chief ministers are likely to coincide with their ethnic home-grounds as well, implying that under a political setup where individuals vote on ethnic lines rather than actual performance, political leaders do not have to invest as many resources in the development of their regions to maximize the likelihood of re-election. In other words, regardless of performance, ethnically aligned voters are going to re-elect leaders with similar ethnic background. This equilibrium is likely to not hold for political leaders contesting elections from non-native regions, creating pressure on them to actually enhance regional development to garner votes in subsequent elections.

Before proceeding further, we highlight two important caveats to the analysis offered above. First, following the previous literature, we also assume that a candidate is weakly more likely to belong to the same ethnic group as his electoral district's population if he is born in that district than if he is born outside it. If this assumption is satisfied, one can use whether a candidate was born in his electoral district as a proxy for ethnic affinity with voters. For instance, this is the main ingredient in the approach taken by Hodler and Raschky (2014) and subsequent papers as well. However, one would need much more finely grained data to empirically test this assumption.

Second, we do not model the candidate decision regarding which constituency to run in. Rather, we study the CM's transfer decision conditional on contesting from that district. As long as there are no systematic differences between those who run inside their district or outside their birth district, selection effects are not likely to contaminate our results. For instance, if non-birth CMs are more politically astute they can be selecting constituencies that were already trending up in terms of economic activity, which could spuriously present itself as a positive treatment effect in our analysis. Columns (2) and (3) of Table 2 show that there are no statistically significant pre-trends for non-birth CMs and the point estimate is in fact negative. This allays concern that the higher estimated effect in non-birth CM constituency is not likely to be a result of the CMs decision to run from that constituency.

A recent set of papers has raised concerns regarding the estimation of treatment effect parameters in difference-in-differences (DiD) design. For instance, Goodman-Bacon (2018) shows that in such designs the estimating specification, like equation (1) above, is aggregating multiple 2x2 DiD comparisons with the regression assigning different weights across these

Table 1: Chief Minister Tenure and Night Light Activity in Own Constituency

	Contemporaneous Specification			First Lag Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.122***	0.119***	0.119***	0.088***	0.078**	0.087**
	(0.033)	(0.044)	(0.044)	(0.032)	(0.036)	(0.037)
Three Years Before	–	- 0.040	- 0.022	–	- 0.056	- 0.020
		(0.047)	(0.042)		(0.044)	(0.035)
Three Years After	–	0.027	0.040	–	- 0.020	- 0.047
		(0.041)	(0.054)		(0.031)	(0.034)
Linear Pre-trend	–	–	- 0.020	–	–	- 0.037
			(0.028)			(0.030)
Linear Post-trend	–	–	- 0.015	–	–	0.029
			(0.022)			(0.020)
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

comparisons. Ideally, we want treated units to be compared only to the never treated units. However, Goodman-Bacon (2018) establishes that when early-treated units serve as 'control' for later-treated units due to change of treatment status of the latter in certain 2x2 comparisons, it can induce biases in the estimated effect. This is particularly problematic when treatment is staggered as in our setting. To allay such potential concerns, we implement his diagnostic procedure and find that in our study the treated vs never-treated comparison gets a 0.996 weight with a slightly higher estimated treatment effect of 0.162 compared to our baseline effect of 0.122.[22] The problematic comparisons, which Goodman-Bacon (2018) calls timing-only, i.e. where both treatment and control groups are treated and the variation comes from a change in treatment status only, get close to zero weights in our setting. This is not surprising, since a vast majority of constituencies never become CM-constituencies hence there always remains a big pool of never treated units in the sample. In other words, our setting does not suffer from the concerns raised in Goodman-Bacon (2018), which gives us more confidence in the validity of our approach.

Finally, it is imperative to discuss the appropriate level of clustering for standard errors in the above employed specifications. Recent work by Abadie, Athey, Imbens, and Wooldridge (2017) has argued to cluster standard errors at the level at which treatment is administered in the setting at hand. Since this is at the assembly constituency level, the above results and all later specifications follow their advice and cluster at the constituency level. They also argue that clustering at more aggregate levels, say at the state level as argued by Cameron

[22] We use the Stata command provided by Goodman-Bacon et al., 2019 to perform this part of the analysis. We thank an anonymous referee for pointing us in this direction.

Table 2: Night Light Activity by CM's Constituencies and Birth District

	Non-Birth District			Birth District		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.189***	0.195***	0.195***	0.049	0.045	0.049
	(0.054)	(0.070)	(0.070)	(0.030)	(0.042)	(0.041)
Three Years Before	–	- 0.068	- 0.047	–	- 0.014	0.034
		(0.080)	(0.055)		(0.045)	(0.045)
Three Years After	–	0.080	0.095	–	0.003	0.017
		(0.067)	(0.061)		(0.035)	(0.035)
Linear Pre-trend	–	–	- 0.019	–	–	- 0.035
			(0.061)			(0.017)
Linear Post-trend	–	–	- 0.017	–	–	- 0.017
			(0.040)			(0.016)
Observations	54,536	54,536	54,536	54,536	54,536	54,536

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

and Miller (2015), for instance, may result in overly conservative confidence intervals. Nevertheless, for the sake of robustness we implement the wild-cluster bootstrap routine, due to the small number of states in India, and present the results in appendix table A.2. The reported p-values using the wild-cluster bootstrap do not change the substantive conclusions presented in tables 1 and 2.[23] Results presented in the rest of the paper are also robust to the wild-cluster bootstrap but we do not report them for brevity purposes. In addition to the above, there is a second concern related to appropriate calculation of standard errors: the small number of treatment clusters in our data. We undertake this in section 6.6.1 by implementing a randomization inference routine similar to Conley and Taber (2011).

5.2 Heterogeneity Analysis

5.2.1 By State or Constituency Characteristics

In this subsection we undertake a heterogeneity analysis by various characteristics at the state and individual chief minister level. This exercise will help further dissect the estimated preferential treatment shown by chief ministers toward their own constituencies. Table 3 presents results for both the contemporaneous and first lag specification but only for our most saturated specification, i.e. specification similar to columns (3) and (6) from Table A.3. Panel A splits states by whether they are considered to be corrupt or non-corrupt. We use the standard measure in the literature for this designation the so-called BIMAROU index

[23]We use the Stata command boottest developed by Roodman, Nielsen, MacKinnon, and Webb (2019) to conduct this part of the analysis.

Table 3: Heterogeneity by State Characteristics

	Contemp	First Lag	Contemp	First Lag
	(1)	(2)	(3)	(4)
Panel A: Corruption	Corrupt States		Non-Corrupt States	
CM Tenure Effect	0.189**	0.119	0.092***	0.074***
	(0.087)	(0.085)	(0.028)	(0.029)
Observations	20,672	19,456	33,864	31,872
Panel B: Percent Rural	Rural > 80%		Rural < 80%	
CM Tenure Effect	0.142***	0.108***	- 0.009	- 0.031
	(0.039)	(0.036)	(0.075)	(0.083)
Observations	47,668	44,864	6,868	6,464

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

(Fisman et al., 2014). Column (1) estimates that CM constituencies in corrupt states witness a 20.8 percentage ($\gamma = 0.1886$) growth in night light, which is twice the size of non-corrupt states shown in column (3). This finding makes intuitive sense since the baseline estimated effect is not entirely a result of ethical practices and hence one would expect exactly this pattern *a priori*.

We perform a heterogeneity analysis by splitting sample into two subgroups – corrupt and non-corrupt states. Election rigging is more likely to occur in the states where corruption is higher. We find that chief ministers' transfers to their own constituencies where they got elected from is almost two-fold in corrupt states compared with the non-corrupt states, showing evidences of higher favoritism.

Panel B then splits the sample by degree of rurality. We construct our own data driven measure of rurality by geocoding the proportion of area in each CM constituency that comprises of villages. Results show that chief ministers that belong to more rural home constituencies, direct more funds to their areas. This effect is substantial and strongly significant for the first lag specification as well. The results are also robust to perturbations to our 80% threshold for treating a constituency as primarily rural.

5.2.2 By Chief Minister Characteristics

Based on a Supreme Court order, starting from 2004 all candidates that aspired for political office had to submit disclosure forms detailing important personal information that the Court deemed important to the electorate. These included pre-election details of financial assets and income, academic qualifications as well as details of any criminal cases or convictions

Table 4: Heterogeneity by CM Characteristics

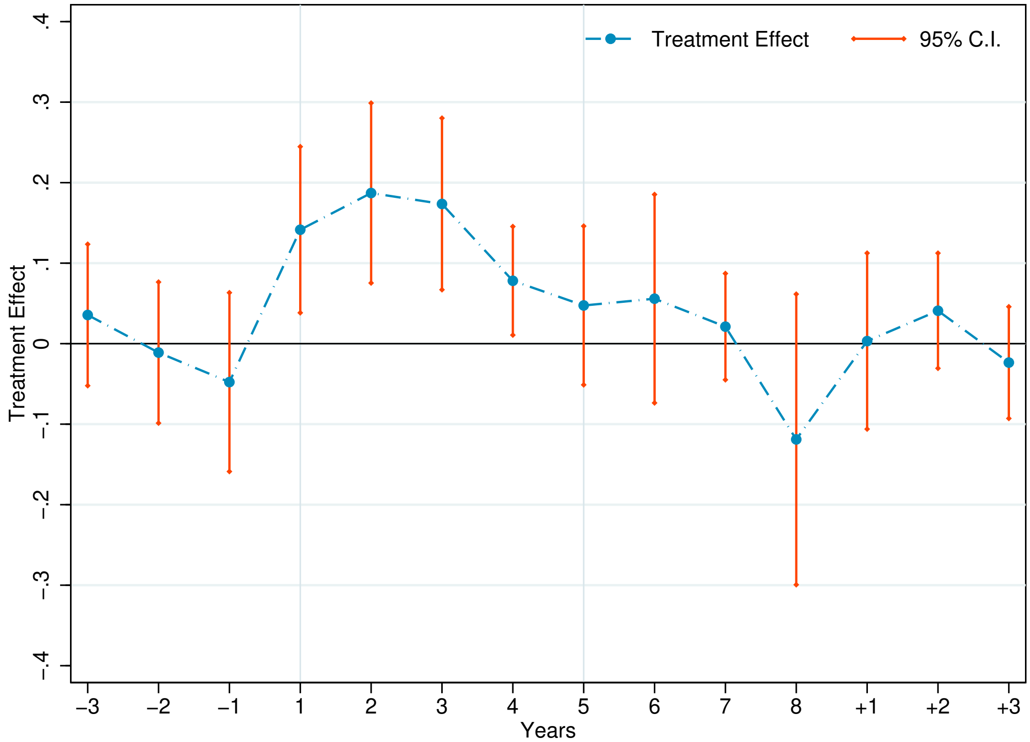
	(1)	(2)	(3)	(4)	(5)
CM Tenure Effect	0.122***	0.154***	0.178***	0.103***	0.103***
	(0.033)	(0.052)	(0.062)	(0.038)	(0.036)
CM*Experience	–	−0.011 (0.014)	–	–	–
CM*Tenure	–	–	−0.011 (0.010)	–	–
CM*College Education	–	–	–	0.051 (0.085)	–
CM*Criminal Record	–	–	–	–	0.020 (0.017)
Observations	54,536	54,536	54,536	54,536	54,536

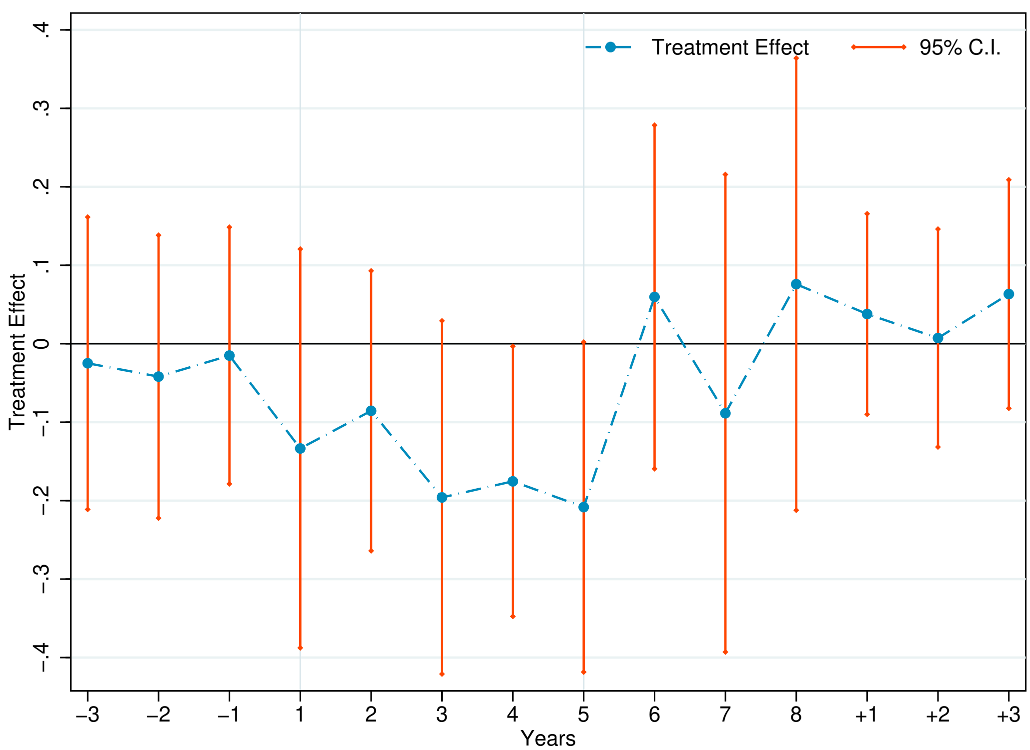
***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

against the candidate. We collect information from these candidate disclosure forms for all chief ministers in our sample. Specifically we construct binary variables for chief ministers with at least a college degree, and whether they have any criminal record prior to filing nomination papers. We also construct continuous variables for overall political experience in years, and for tenure as chief minister as well. Table 4 first reproduces results from our baseline specification in column (1). We then interact the four characteristics mentioned above with our baseline treatment variable. Column (2) shows that inexperienced politicians divert slightly more funds to their own constituencies on assuming the position of chief minister, however, the interaction term itself is statistically insignificant. We find a similar results for chief ministers at the start of their tenure as well. We analyze the dynamics of CM tenure in more detail in the next subsection. Column (4) provides suggestive evidence that more educated CMs divert more funds to their constituencies. The baseline effect falls to 0.103 or 10.9 percentage with the interaction effect of a college degree being 0.051, although this is statistically insignificant. For politicians, with a criminal record the baseline effect is again few percentage points lower than our main findings, although we don't have enough power to identify the interaction coefficient itself. Overall these results show the existence of some heterogeneity in the estimate effect of preferential treatment of chief ministers shown toward their home constituency, however, because of the small sample number of treated units in these sub-categories results are imprecise.

Figure 2: Dynamic Treatment Effects of CM Tenure - Overall

(a) Chief Minister - Overall





(b) Opp. Leader - Overall

5.3 Dynamic Treatment Effects

In this section we implement a standard dynamic treatment effect specification to unpack how the estimated effect varies by each year of tenure of the chief minister. As is common in the difference-in-differences literature, a by-product of such an exercise is a visualization of the pre-treatment common trends assumption as well (see for instance, Autor, 2003). Figure 2 presents the estimated coefficient for each year separately, starting from 3 years before a constituency had its representative elected as the chief minister, and up to 3 years after the tenure of the chief minister.[24] We have only two chief ministers in our sample who remained in power for more than 9 years, we therefore top code years in power to 8. There are three findings worth highlighting in Figure 2(a). First, we find no evidence of future CM constituencies growing differentially with respect to the rest of the constituencies in the three years before assuming power. This corroborates our results in the above analysis as well. Second, the estimated treatment effect is concentrated in the first three to four years of the tenure of the chief minister, and diminishes there after. Finally, we find no evidence of long term gains in economic activity after the chief minister has gone out of power signifying that chief ministers might be focused on maximizing short term objectives with respect to their re-election bids.

We next explore the existence of any predatory practices undertaken by the chief minister toward their main rivals, in addition to the preferential treatment that they exhibit toward their home constituencies. As mentioned earlier there is substantial anecdotal evidence for this phenomenon with prominent opposition politicians regularly making allegations in this vein against sitting chief ministers. Although it might be difficult to ascertain whom a given chief minister considers their prime rival, one political portfolio that we can consider is the leader of the opposition in the state assembly in each respective chief minister's tenure. The opposition leaders usually are the heads of the second largest political party in the state and in most instances are the main contender for the top position in government for their respective parties. We implement a similar analysis as above for these opposition leaders. Figure 2(b) provides suggestive evidence that some form of predatory politics might be at play in our institutional setting. Constituencies that opposition leader are elected from perform similar to the rest pre-treatment but start trending downward moment their representative becomes the opposition leader in the state assembly. Although our point estimates are similar in magnitude to the effect sizes in Figure 2(a), but due to a fewer number of opposition leaders in our sample, the coefficients are imprecisely estimated.

[24] We repeat this analysis and implement a complete event-study style difference-in-differences by estimating separate coefficients for every time period, omitting the year before treatment. Appendix Figure A.1 provides the results from this exercise and as can be seen our CM tenure effects remain robust to this change.

Table 5: Chief Minister Tenure and Night Light Activity - Neighboring Areas

	Baseline	15 km	25 km	35 km	District	LS
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.122***	0.088**	0.072	0.060	0.013	0.077***
	(0.033)	(0.036)	(0.062)	(0.064)	(0.030)	(0.024)
Observations	54,536	54,536	54,536	54,536	8,483	6,565

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

5.4 Spillovers

There is a substantial literature in economics that has studied the local economic effects of various public policies or other treatment regimes that can induce localized spillovers. While a complete analysis of regional spillovers is beyond the scope of this paper, in this section we provide suggestive evidence of localized effects accruing to areas beyond just the CM constituency itself. For instance, if a CM constituency is getting electrified then power infrastructure might have to pass through nearby constituencies creating the potential of developmental spillovers. Even without these mechanical spillovers, one might expect standard regional fiscal multipliers to manifest in economic growth for neighboring areas as well. On the other hand, CMs might also target broader areas around their constituencies, especially if they are also strategically important. Feyrer, Mansur, and Sacerdote (2017) provide an intuitive and straightforward way of studying potential spillovers when treatment is administered to a given geographic area of interest. In their analysis of the fracking boom in the US, they study local spillovers accruing to areas beyond the county of interest by drawing circles of increasing radii around the centroid of the treated county. In Table 5 columns (2) to (4), we implement their approach for our setting. We draw circles, of 15, 25, and 35 km radius from the center of each constituency and calculate night light intensity within these circles. Treatment is defined as the circle whose centroid lies in a CM constituency. We see a slightly smaller estimated effect of around 0.088 percentage points in column (1) which falls to around 0.060 and becomes insignificant for the 35 km radius.[25] In other words, any potential economic spillovers dissipate the farther away we go from the CM constituency.[26]

Another common approach in the literature is to aggregate the spatial unit of analysis to

[25] We only implement the baseline regression of column (1) of Table 1 here since we found no evidence of pre-trends there.

[26] James and Smith (2020) point out that this approach can potentially overestimate spillovers since treated counties in Feyrer et al., 2017 farther away can have inward spillovers to other treated counties hence amplifying the true spillover. We are less likely to suffer from this concern since each state has only one treated or CM constituency. Furthermore, neighboring constituencies of two different treated constituencies across states rarely overlap hence inward spillovers are not likely to intersect either.

a larger geographic entity and rerun the analysis to check if the effect persists. For instance, Hodler and Raschky (2014); Feyrer et al. (2017) among others. In column (5) we aggregate our data to the administrative district level, which has around 6 to 7 LACs in it. Our estimated coefficient falls close to zero at this level of aggregation. This can imply two things: 1) either any spillovers that exist are operating at a really local level, i.e. immediate vicinity of the treated constituency, or 2) if politicians are engaging in strategic behavior due to political expediency concerns then they are differentially investing in only those nearby constituencies that can help them politically and this can be difficult to capture with aggregation at the district level since it is an administrative agglomeration. To explore this further, column (6) aggregates the data to the federal constituency level or Lok Sabha (LS), which also contains around 6 to 7 LACs on average, albeit a different mix than the district agglomeration.[27] Here we estimate an effect size of 0.077 ($p < 0.01$) implying that some spillovers do operate beyond just the CM constituency and may have a potential strategic element to them. In the rest of this section, we dig a little deeper into this assertion. In the above analysis we took the approach to aggregate our analysis to various levels while keeping the CM constituency in the estimation sample. Another alternative approach is to conduct a so-called donut analysis where the treated unit is dropped and units bordering it are considered as the treated zone. For instance, Hornbeck and Keskin (2015) do a similar analysis to study the local economic effect of the availability of a source of groundwater to areas outside the treated area. In our setting this is is visualized with an example in Figure 3, where Latur, the constituency of the chief minister of Maharashtra, has seven immediate neighbors. We drop the actual CM constituency from this analysis and then either consider all 7 neighbors as treated units or 'slice' the donut in interesting ways to uncover any heterogeneity in estimated spillovers. Columns (1) and (2) estimate a CM Tenure coefficient of 0.049 ($p < 0.01$) for all neighbors, translating into a 5 percentage increase in night light activity for neighboring constituencies relative to the control constituencies. The remaining columns of Table 6 try to shed light on the potential mechanism for these spillovers. We first restrict to the Lok Sabha (LS) or federal assembly constituency that a given CM constituency lies in. Next we assign treatment status to only those neighbors of the CM constituency that fall in the same LS. This is shown by the slanted lines constituencies in figure 3. Our motivation for this is based on a persistent pattern in the Indian political landscape: a substantial number of chief ministers have career trajectories of moving 'upward' to federal government either as ministers in federal cabinets or as the prime minister itself. If chief ministers have these long term goals, then it would be helpful to strategize and develop areas in potential LS seats that they might contest from

[27] This reduces the distinct number of geographic units from around 3200 LACs in our main analysis to 500 federal constituencies here.

Figure 3: Neighboring Constituencies to the CM's Own Constituency - Latur

Table 6: Chief Minister Tenure and Night Light Activity - Neighboring Constituencies and Lok Sabha (LS) of CM Constituency

Neighbor Definition	All		Same LS		Different LS		Non-Neighbor Same LS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CM Tenure Effect	0.049**	0.049***	0.071**	0.071**	0.026	0.026	0.001	0.005
	(0.017)	(0.018)	(0.028)	(0.028)	(0.027)	(0.027)	(0.029)	(0.029)
Three Years Before	- 0.006	- 0.021	0.008	0.002	- 0.020	- 0.043	- 0.015	- 0.021
	(0.017)	(0.020)	(0.026)	(0.030)	(0.022)	(0.027)	(0.025)	(0.026)
Three Years After	0.004	0.005	0.005	0.002	0.001	- 0.018	- 0.006	- 0.028
	(0.016)	(0.024)	(0.020)	(0.027)	(0.025)	(0.026)	(0.023)	(0.028)
Linear Pre-trend	–	0.016	–	0.007	–	0.025	–	0.011
		(0.011)		(0.016)		(0.015)		(0.014)
Linear Post-trend	–	-0.001	–	0.004	–	0.023	–	0.027
		(0.013)		(0.013)		(0.015)		(0.016)
Observations	53,635	53,635	53,635	53,635	53,635	53,635	53,635	53,635

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

in the future. Columns (3) and (4) assign treatment to only these constituencies, among the set of neighbors, and present evidence for precisely such strategic considerations. Neighbors that lie in the same LS constituency witness around a 7 percentage increase in night light intensity, similar to the findings above. However, those neighbor that belong to different LS constituencies (dotted areas in figure 3) show an increase of around 2 percentage but this is statistically insignificant.

For completeness, the final two columns of Table 6 repeat the analysis for non-neighboring constituencies that lie in the same LS constituency as the CM constituency, the point estimates are close to zero and statistically insignificant. This provides suggestive evidence that chief ministers might be balancing short-term state assembly level gains versus long-term aspirations of running for federal level political portfolios.

5.5 State and Federal Cabinet Ministers

Our analysis so far has focused on the constituency of the holder of the highest office in state governments in India. Similarly, as outlined before previous literature has focused on heads of government at the country level. However, there are other important portfolios in parliamentary setups as well, for instance, federal and state cabinet ministers who also might engage in distributive politics. In the Indian setup the federal government appoints around 30 ministers to the cabinet who are responsible for various portfolios. These ministers can either be elected members of the Lok Sabha, the Indian Parliament, or can be unelected. We focus on the elected ministers and repeat the above analysis at the Lok Sabha constituency level. Similarly, state governments also form cabinets where ministers are primarily drawn from the elected assemblies. We hand collected data on federal and state cabinet ministers along with their birth districts and elected constituencies. Our data includes information on 46 state cabinet ministers with portfolios of Home, Revenue and Finance, and 39 federal cabinet ministers.

At the outset, it is not clear whether cabinet ministers are likely to divert funds to their constituencies similar to the CMs. While federal ministers might face similar re-election incentives, they are also likely to be judged for achievements at a much broader level. Similarly, given that one does not have to be an elected member of parliament to become a minister, re-election pressure are likely to be strictly weaker than in the case of chief ministers. Also, the items of expenditure in the State list, over which a CM has discretionary powers, is much more comprehensive than the items of targetable expenditure items controlled by any single state cabinet minister. Table 7 presents results from our baseline specifications implemented at the Lok Sabha level. Here a constituency is considered treated if its Lok Sabha member

Table 7: Cabinet Minister Tenure and Night Light Activity in Own LS Constituency

	State			Federal		
	(1)	(2)	(3)	(4)	(5)	(6)
Minister Tenure Effect	0.000	- 0.017	- 0.014	- 0.008	- 0.000	- 0.000
	(0.024)	(0.034)	(0.034)	(0.032)	(0.044)	(0.044)
Three Years Before	–	- 0.026	- 0.021	–	0.016	- 0.027
		(0.029)	(0.030)		(0.027)	(0.028)
Three Years After	–	- 0.043	- 0.045	–	0.015	0.018
		(0.036)	(0.033)		(0.044)	(0.046)
Linear Pre-trend	–	–	0.004	–	–	0.040***
			(0.018)			(0.014)
Linear Post-trend	–	–	- 0.001	–	–	- 0.001
			(0.013)			(0.015)
Observations	54,307	54,307	54,294	6,565	6,565	6,565

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

holds a federal cabinet portfolio. It is immediately evident that these constituencies do not undergo any differential development compared to the control constituencies. The estimated point estimate is close to zero in both the contemporaneous and the first lag specification. However, unlike the CM constituencies there is some evidence that these constituencies had a positive pre-trend before their members became federal ministers. Overall it seems that state CMs are much more likely to divert funds for the development of their own constituencies compared to federal ministers.[28]

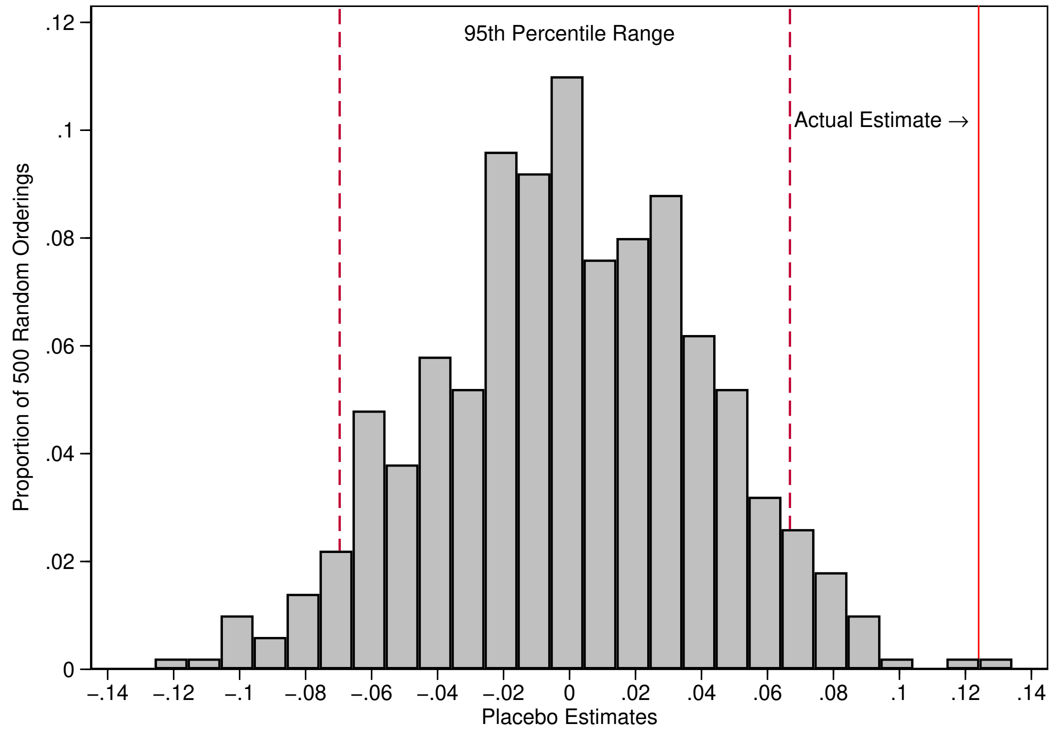
5.6 Robustness Checks

5.6.1 Randomization Inference

One concern that can plague the above analysis is the validity of our employed statistical inference procedures. So far in the analysis we clustered the standard errors at the constituency level using standard methods. However, recent literature has raised concerns about the validity of standard errors in difference-in-differences studies especially when the number of treated clusters or observations within them are small relative to the sample size.

[28]It is indeed possible that some other channel of group affinity could explain why chief ministers make significantly more transfers to their electoral constituencies. It will be interesting to examine what other form of group loyalties could be at play in determining transfers. This would require much more fine-grained data on various constituency attributes. We leave this for a future project.

Figure 4: Permutation Tests: Random Orderings of CM Constituencies



This applies to our setting here as well since each state has only one CM constituency per electoral cycle, resulting in less than 1% of the observations as treated. In this section we implement a randomization inference style procedure following recommendations made in Conley and Taber (2011).[29] The idea here is straightforward: we randomly assign treatment status to control constituencies belonging to the same state, i.e. we treat non-CM constituencies as if they were CM constituencies.[30] These placebo assignments, however, follow the same tenure length as the actual chief minister did for a given state and tenure combination. We then estimate equation (1) based on this randomly ordered dataset and repeat this process for 500 random draws. Figure 4 presents the results from this exercise. As is immediately evident, the placebo estimates are centered around zero and our actual estimate (column (1) Table A.3) is well to the right of the 95th percentile of this distribution. We also repeat this exercise by randomly drawing from only those control constituencies that belong to the political party of the chief minister. Results are similar to Figure 4 although

[29]Similar methods of inference are now being applied regularly in the empirical literature, for instance, see Bursztyn and Jensen (2015) for a recent implementation.

[30]The correct CM constituency is part of the sample and hence theoretically can be reassigned treatment status as well in a given iteration.

Table 8: Chief Minister Tenure and Night Light Activity - Interactive Fixed Effects

	Standard	Number of Factors				
	0	1	2	3	4	5
CM Tenure	0.138***	0.131***	0.120***	0.120***	0.112**	0.114**
Effect, γ	(0.037)	(0.040)	(0.043)	(0.040)	(0.044)	(0.050)
Observations	54,536	54,536	54,536	54,536	54,536	54,536

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All specifications include an additive constituency fixed effect and a year fixed effect. Standard errors are clustered at the constituency level.

the distribution of placebo estimates moves slightly to the right as expected.[31] Overall this exercise provides credence to the conclusion reached in our main analysis that chief ministers are indeed differentially developing their own constituencies and potential concerns about inference procedures are not influencing our findings.

5.6.2 Interactive Fixed Effects

As a second robustness check, we next present results from the interactive fixed effects (IFE) specification outlined in section 4.2. As outlined there, the IFE models are capable of controlling for more general forms of unobserved heterogeneity by allowing individual constituency to respond differentially to common unobservable shocks. In practice, IFE setups require the researcher to specify the number of factors (r) to be included in the model. While there are statistical tests proposed to inform the optimal number of factors (e.g., Bai and Ng (2002)), there are also concerns regarding the stability of these tests (Onatski et al., 2013). Therefore, applied researchers using these methods generally vary the number of factors included in the model and check for the stability of the parameter of interest across specifications (e.g, Kim and Oka, 2014; Gobillon and Magnac, 2016). Table 8 presents our results from this exercise. We first estimate a standard linear panel data model, which included only constituency and year fixed effects and present results only for the contemporaneous specification. The point estimate in the first column of Table 8 is slightly higher compared to our preferred specification in column (3) of Table A.3. This is expected since the latter assumes a prior structure for differential trends for the CM constituencies as defined in equation (2). The remaining columns in Table 8 then vary the factors between 1 to 6. As is evident, our estimated effect is very stable across specifications and is similar to the baseline finds in section 5.1. This signifies that our setup is likely capturing the causal effect

[31]We do not plot these results for brevity purposes.

on local economic development for a constituency whose member of parliament is elected as the Chief Minister as opposed to a differential response to some underlying unobservable common shock.

6 Discussion and Conclusion

This paper contributes to the literature on the nature of distributive politics in legislative systems with single member districts. Specifically, we seek to understand whether constituencies represented by powerful politicians get a more favorable treatment relative to other constituencies. We use night light intensity as a measure of development, and show that during the tenure of the chief minister (CM) their home constituencies enjoy on average 13 percent higher night light activity compared to other constituencies. The estimated effect peaks during the second year of a chief minister's tenure but do not persist in the long-run after the CM has left office. These results are not confounded by differential 'pre-treatment' development trajectories for constituencies represented by chief ministers and regular members of state legislative assemblies.

Ethnic affinity between the leader and his/her constituency, for instance proxied by the birth region of the leader, is often cited in the literature as a plausible explanation for such favorable treatment. However, we find that the increased night-light effect is stronger when a CM's constituency lies *outside* his/her birth district. In particular, a constituency that does not lie in the birth district of the chief minister witnesses an increase of over 20 percentage points when its elected member is the CM. The analogous effect for those CM constituencies in their actual birth district is under 5 percentage and statistically insignificant. Thus, while both political expediency as well as ethnic favoritism are at work, it is former that seems to be the dominant effect.[32]

One can conjecture the reasons for our findings. One possibility, consistent with anecdotal evidence, is that a CM's popularity in his/her own constituency is an indicator of their performance or ability, which is then used by the larger party leadership in deciding whether to continue with the chief minister in future. If a CM constituency lies in their birth region,

[32] The relative prevalence of ethnic vis-a-vis political favoritism will differ by the quality of democratic institutions. It seems plausible that in countries with low quality of democratic institutions, in which elections can be rigged, politicians engage in ethnic favoritism with impunity, but see no need for political favoritism. As democratic quality improves to a moderate level, ethnic favoritism is crowded out by the need to appease a majority of local constituents using pork-barrel spending. And, as there is further improvement in institutional quality, political favoritism by leaders also gets curbed. The relative prominence of political favoritism over ethnic favoritism that we find seems to be consistent with India having moderately high quality democratic institutions. Note that India scores a 9 out of 10 on the PolityIV Index of democratic institutional quality, the only democracies with a better rank are the "Western" developed country democracies. (See http://www.systemicpeace.org/vlibrary/GlobalReport2017.pdf)

then they may naturally enjoy more popularity given the ethnic affinity. However, when this is not the case, the CMs need to work harder, by providing more benefits, to 'buy' popularity. Similarly, another indication that career concerns rather than ethnic affinity are likely to motivate the CM's choice of distributive policies is evidenced by the fact that among constituencies neighboring their current electoral constituency, those which overlap with the same federal constituency exhibit greater night light activity relative to those which do not. This suggest that the chief minister may be cultivating his/her popularity with an option of entering federal politics in future.

Overall, our results provide evidence that at least in the case of India, ethnic or familial affinity to geographic regions is not a primary determinant of differential allocation of development funds by powerful political leaders. Instead we find mechanisms based on political expediency on part of these leaders as more plausible. These seem to extend to concerns based in terms of both maximizing the chances of re-election from the same constituency, as well as developing affinity with voters in those regions that are likely to help them climb the political ladder.

Interestingly, we find that the night-light effect tends to be a short-run phenomenon, and no long-run effect on night-light is discernible. This suggests that regional favoritism tends to take the form of short term transfers or policy favors rather than investment in infrastructure or local public goods. The finding that, in the Indian context, politically channeled benefits tend not to be allocated to infrastructure or local public goods provision is well-documented in Asher and Novosad (2017). They conjecture that this may be because the control over local regulatory processes and the ability to remove bureaucratic gridlock provide politicians with a relatively "cheap policy tool" to direct resources to target areas. These cheap policy tools are as easy to take away as they are to give. This fact, combined with a short average duration of CM tenure (under 4 years), could be the driver of our findings. Our findings are also consistent with our view that political expediency is the more dominant explanation of regional favoritism; if transfers were motivated by ethnic affinity, one would expect them to be made in a more long-lasting form.

Although the primary aim in this paper was to test the hypothesis of ethnic favoritism, it is possible that some other channel of group affinity could explain why non-birth CMs make significantly more transfers to their electoral constituencies. It will be interesting to examine what other form of group loyalties could be at play in determining transfers. This would require much more fine-grained data on various constituency attributes.

Finally, while our paper sheds light on transfers by powerful politicians at the state level, it would be interesting to explore whether similar dynamics exist at the local government level as well, such as municipal and village councils. We leave this question for future research.

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Figure A.1: Dynamic Treatment Effects of CM Tenure - All Time Periods

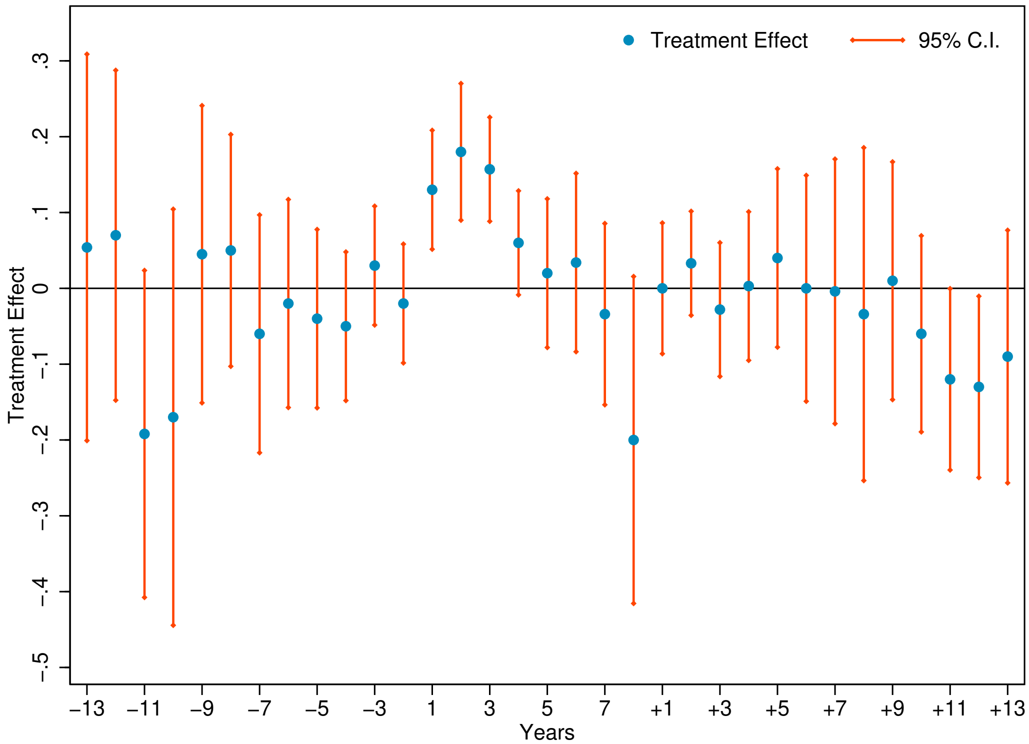

Table A.1: Chief Minister Tenure and Night Light Activity in Own Constituency - Trends

	Contemporaneous Specification			First Lag Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect, γ	0.122***	0.122***	0.121***	0.088***	0.088**	0.086**
	(0.033)	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)
LAC specific linear trend	×	✓	✓	×	✓	✓
LAC specific quadratic trend	×	×	✓	×	×	✓
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

Table A.2: Chief Minister Tenure and Night Light Activity - Wild Bootstrap p-values

	Contemporaneous Specification			First Lag Specification		
Panel A: Baseline Results	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect, γ	0.122***	0.119***	0.119***	0.088***	0.078**	0.087**
	(0.033)	(0.044)	(0.044)	(0.032)	(0.036)	(0.037)
	[0.000]	[0.008]	[0.008]	[0.017]	[0.066]	[0.033]
Panel B: Birth vs Non-Birth	Non-Birth District			Birth District		
CM Tenure Effect	0.189***	0.195***	0.195***	0.049	0.045	0.049
	(0.054)	(0.070)	(0.070)	(0.030)	(0.042)	(0.041)
	[0.000]	[0.010]	[0.009]	[0.147]	[0.298]	[0.284]
Three Years Before	×	✓	✓	×	✓	✓
Three Years After	×	✓	✓	×	✓	✓
Linear Pre-trend	×	×	✓	×	×	✓
Linear Post-trend	×	×	✓	×	×	✓
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. (Standard errors clustered at the constituency level following prescriptions from Abadie, Athey, Imbens, and Wooldridge, 2017). [p-values from wild cluster bootstrap at the state level based on Cameron and Miller, 2015)

Table A.3: Chief Minister Tenure and Night Light Activity in Own Constituency

	Baseline			Control: Power Const			Control: Opposition Const		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CM Tenure Effect	0.122***	0.119***	0.119***	0.069*	0.049	0.046	0.158	0.181**	0.181**
	(0.033)	(0.044)	(0.044)	(0.040)	(0.049)	(0.048)	(0.067)	(0.084)	(0.085)
Three Years Before	–	-0.040	-0.022	–	- 0.050	- 0.008	–	0.001	0.018
		(0.047)	(0.042)		(0.046)	(0.065)		(0.057)	(0.063)
Three Years After	–	0.027	0.040	–	- 0.038	- 0.081	–	0.070	0.090
		(0.041)	(0.054)		(0.066)	(0.095)		(0.056)	(0.074)
Linear Pre-trend	–	–	- 0.020	–	–	- 0.045	–	–	- 0.021
			(0.028)			(0.040)			(0.024)
Linear Post-trend	–	–	- 0.015	–	–	0.058	–	–	- 0.022
			(0.022)			(0.055)			(0.089)
Observations	54,536	54,536	54,536	25,083	25,083	25,083	29,453	29,453	29,453

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All specifications include an additive constituency fixed effect and a year fixed effect. Standard errors are clustered at the constituency level.