# Does Vertical Political Alignment Impact Local Economic Growth? Night-Lights Evidence from India

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**Abstract**

*This paper examines whether vertical political alignment, defined as the scenario in which the national legislator (MP) and the state legislator (MLA) belong to the same political party, improves local economic growth in India. Using Indian election data from 1999 to 2013 and assembly constituency level night lights data as a proxy for economic activity, I implement a regression discontinuity design that exploits close state assembly races to compare constituencies that narrowly achieve alignment with the sitting MP to those that narrowly fail to do so. Across bandwidths, polynomial choices, and control sets, estimated effects on night-lights growth are small and statistically indistinguishable from zero (point estimates range from* $-0.0046$ *to 1.02 percentage point under varying specifications). Supplementary analysis using constituency level data on road construction yields comparable null results, with no evidence of increased public goods provision under political alignment. Taken together, the findings indicate that vertical political alignment does not produce measurable aggregate gains in local economic activity, challenging the 'Double Engine' governance rhetoric that has become increasingly prominent in India's political discourse.*

## 1 Introduction

Countries with a federal structure decentralize political and administrative authority across national, state, and local governments. Such multi-tiered arrangements are intended to bring government closer to citizens, improve accountability, and enhance responsiveness. Yet, decentralization also creates the possibility of political alignment or misalignment across tiers, wherein elected representatives at different levels belong to the same (or different) party. Importantly, the form and consequences of such alignment vary across countries, reflecting differences in constitutional design, party systems, fiscal federalism, and intergovernmental bargaining rules, which result in some alignment configurations being more studied and better understood than others.

There is a rich body of work documenting the role of political alignment across different tiers of government. Evidence from India shows that alignment between state and federal governments increases discretionary federal grants (Arulampalam et al., 2009) and shapes education spending (Khemani, 2003), while in the United States, representation influences federal outlays (Levitt and Snyder, 1995). Similar patterns appear elsewhere: Spanish municipalities aligned with higher-tier governments receive larger transfers (Solé-Ollé and Sorribas-Navarro, 2008), and aligned mayors in Brazil obtain greater pre-election funds (Brollo and Nannicini, 2012). More recent studies move beyond allocations to outcomes, suggesting that decentralization and party structures can shape public-goods provision and local development (Enikolopov and Zhuravskaya, 2007a; Ponce-Rodríguez et al., 2016). Nevertheless, the external validity of these results is limited. Alignment effects hinge on institutional features such as the degree of fiscal and administrative decentralization, the discretion embedded in intergovernmental transfers, party organization and discipline, coalition structures, and electoral rules, making it difficult to generalize findings across tiers within a country, let alone across countries.

In recent years, the idea of "double engine governance" has gained considerable traction in India's political discourse. Coined as a campaign slogan, it conveys the notion that development proceeds faster when both the central and state governments are controlled by the same political party, much like two synchronized engines pulling in the same direction. The phrase has been widely used in election rallies and media narratives, resonating with voters by offering a simple metaphor for political alignment across levels of government. Its growing prominence reflects both the salience of centre–state relations in shaping policy outcomes and the increasing emphasis by parties on projecting alignment as a pathway to faster growth and more efficient governance.

Theoretically, alignment across tiers can cut both ways. On the positive side, aligned representatives may reduce transaction costs, ease administrative clearances, and coordinate the joint financing of projects, thereby enabling faster delivery of infrastructure and public goods. On the negative side, alignment may encourage favoritism, weaken the opposition's ability to monitor incumbents, and facilitate the diversion of resources toward partisan priorities. The net effect of political alignment on local development is therefore ambiguous and warrants empirical investigation.

In this paper, I study India's federal system and ask whether vertical political alignment between a constituency's Member of Parliament (MP) and its Members of the Legislative Assembly (MLAs) causally improves local economic development. India's electoral map comprises parliamentary constituencies for national elections and assembly constituencies for state elections. Each parliamentary constituency elects one MP to the national legislature, while the same territory is subdivided into assembly constituencies that elect MLAs to the state legislature. The national and state elections are independent and governments are formed by parties that secure legislative majorities at each tier. Because MPs and MLAs are elected independently, the same geographic area can, at any point in time, exhibit either alignment (MP and MLAs from the same party) or misalignment.

To estimate the causal effect of MP-MLA political alignment on local development, I employ a regression discontinuity (RD) design that exploits close state assembly elections. The forcing variable is the MLA's margin of victory, and the treatment is whether the winning MLA shares party affiliation with the MP representing the same parliamentary constituency. By focusing on narrow electoral contests, the design compares otherwise similar constituencies that differ only in their alignment status, providing credible identification of causal effects. I study two outcomes of local economic development: growth in night light intensity, a widely used proxy for granular economic activity, and administrative measures of road construction.

The findings indicate that MP-MLA political alignment has, at best, limited effects on both night-lights growth and road development. Across multiple specifications, I find no robust or economically meaningful impact of vertical political alignment on local economic activity. Despite theoretical expectations that alignment should reduce political frictions and foster cooperation, the evidence suggests that in practice such alignment is not a decisive determinant of development outcomes. These null results are themselves informative: they highlight the limits of partisan coordination in a federal democracy where authority is fragmented and the discretionary resources of individual legislators are modest relative to overall public spending.

This paper makes three key contributions. First, it provides the first causal evidence on the development consequences of MP–MLA political alignment, moving beyond fiscal allocations to realized outcomes and directly testing the empirical validity of the "double engine governance" rhetoric in India. Second, it contributes to the empirical literature that leverages close elections within a regression discontinuity (RD) framework, using narrow assembly races to identify the local effects of vertical alignment. Third, it adds to the growing body of work that uses satellite-based night-lights data as a proxy for local economic activity to evaluate the developmental impact of political institutions and alignments.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 reviews the related literature. Section 4 introduces the data. Section 5 presents the empirical strategy. Section 6 reports the main results, identification and placebo tests, and heterogeneity analysis across states and contexts. Section 7 extends the analysis to public-goods provision by examining road construction outcomes at the assembly constituency level. Section 8 concludes.

# 2 Institutional Background

## 2.1 Elections and Elected Representatives

India is a federal parliamentary republic in which state-level institutions broadly mirror the national architecture. At the national level, the bicameral Parliament comprises the House of the People (Lok Sabha) and the Council of States (Rajya Sabha). The members of the House of the People are directly elected from single-member parliamentary constituencies under first-past-the-post rules, while the Council of States members are elected by states using proportional representation (single transferable vote). Council of States members do not represent territorial constituencies and do not contribute to our study. There are 543 parliamentary constituencies in India, as shown in Figure 1.

At the state level, voters elect Members of the Legislative Assembly (MLAs) from single-member constituencies, also under first-past-the-post rules. Some states additionally maintain an upper chamber, the legislative council, but the directly elected legislative assemblies are the primary body of interest. In total, there are roughly 4,100 assembly constituencies in the 28 states of India (Figure 2).

India's electoral geography is nested: each parliamentary constituency encompasses multiple assembly constituencies, often referred to as "assembly segments." Voters in each segment elect an MLA, and the same territory collectively elects an MP. The number and composition of assembly segments within a parliamentary seat are determined by the Delimitation Commission of India (1973,2008). This nesting is central to my analysis: it allows me to map each assembly constituency to its parent parliamentary constituency in each year and study vertical political alignment within the same geographic unit. Figure 4 shows the Bolpur Parliamentary Constituency, which is one of the 42 Parliamentary seats in West Bengal and encompasses 7 assembly constituencies. The number of assembly constituencies within a parliamentary constituency can vary by state.

The national and state elections in India are not synchronized. The parliamentary elections have a maximum five-year term (subject to early dissolution), and each state assembly follows its own five-year cycle, which may also end early if a government loses confidence. As a result, most state elections occur off-cycle. This staggering means that at any point in time, an assembly constituency is represented by an MP elected in year $t^{MP}$ and an MLA elected in year $t^{MLA}$. The overlap yields between zero and four full years of political alignment. Figure 5 uses 4 state assembly elections and the 2004 parliamentary elections to show how clean overlaps are calculated for analysis in this paper. My design leverages this natural variation: conditional on the MP's party being predetermined at the time of the state election, close MLA races provide quasi-random assignment of alignment, thereby creating aligned (or misaligned) cases that allow me to estimate its impact on local area development in this context.

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### 2.2 MP and MLA Duties

Elected representatives in India hold legislative, budgetary, and oversight responsibilities with partly overlapping domains. Members of Parliament (MPs) legislate on Union subjects, scrutinize national ministries and budgets, and channel constituency resources through instruments such as the Members of Parliament Local Area Development Scheme (MPLADS). Members of Legislative Assemblies (MLAs) legislate on state subjects, shape state budgets and departmental priorities, and monitor the implementation of state programs.

In practice, influence extends beyond formal mandates. A growing literature shows that MLAs affect bureaucratic transfers, postings, and promotions, with measurable consequences for administrative responsiveness (Iyer and Mani, 2012; Sukhtankar and Vaishnav, 2015; Asher and Novosad, 2017). Although MPs sit outside the state chain of command, they often exercise de facto influence, especially when their party governs at the state or national level by coordinating with ministers and senior officials.

Bureaucrats therefore respond to signals from both tiers. MPs and MLAs act as intermediaries between citizens and the state: brokering access to programs, shaping project selection and timing, and easing implementation bottlenecks. This dual channel of influence provides a direct mechanism through which vertical co-partisanship (MP–MLA alignment) could affect the level and composition of local development—the hypothesis tested in this paper.

## 3 Related Literature

This paper relates to several strands of work in political economy.

First, it builds on the regression discontinuity (RD) literature that treats close elections as generating quasi-random assignment of winners, enabling credible causal inference about political impacts. Lee (2008) established the foundational design, and subsequent studies have applied it to a wide range of contexts, from incumbency advantage to fiscal transfers. This framework has become central to understanding how electoral outcomes shape policy and performance.

Second, a growing body of research leverages close-election RD designs to study how *politician characteristics* influence development, frequently using night-time lights as an outcome. In the Indian context, Prakash (2019) show that electing criminally accused politicians lowers economic activity (including luminosity) and worsens governance, with follow-up evidence on crime and accountability (Prakash et al., 2024). Relatedly, Makkar (2023) find that electing party defectors alters local growth trajectories, again measured via satellite lights. Complementing these studies, the development literature validates night-time lights as a proxy for subnational growth and welfare

(Henderson et al., 2012; Michalopoulos and Papaioannou, 2014).

Third, this study contributes to work on *political alignment*. A large literature shows that co-partisanship between different tiers of government increases transfers and program allocations. For India, Arulampalam et al. (2009) document how state–national alignment boosts federal grants, and Khemani (2003) show how partisan politics shapes education spending. Similar findings appear elsewhere: U.S. congressional representation affects federal outlays (Levitt and Snyder, 1995), Spanish municipalities aligned with higher tiers receive larger transfers (Solé-Ollé and Sorribas-Navarro, 2008), and Brazilian mayors aligned with the president obtain greater discretionary funds (Brollo and Nannicini, 2012). More recent work extends from allocations to *outcomes*: Asher and Novosad (2017) find that ruling-party representation raises local employment and luminosity, while Bhavnani et al. (2021) and Enikolopov and Zhuravskaya (2007b) show that representation and party structure shape local public-goods provision. This paper adds to that literature by focusing on vertical alignment between MPs and MLAs within the same geographic space—an unexplored dimension of co-partisanship.

Together, these strands highlight three points: (i) close-election RD provides credible causal leverage; (ii) politician traits and party incentives matter for development outcomes; and (iii) alignment has well-established effects on fiscal allocations, but much less is known about its impact on realized local economic activity. This paper addresses that gap by providing the first causal evidence on the developmental consequences of MP–MLA alignment on local growth in India.

# 4 Data and Descriptive Statistics

## 4.1 Data

The primary data for this study come from the Trivedi Centre for Political Data (TCPD), which compiles and cleans election results originally published by the Election Commission of India (ECI). The TCPD dataset is among the most comprehensive sources on Indian elections, covering all state assembly elections from 1974 to 2018 and Lok Sabha elections from the 1950s through 2024. It includes detailed information on every candidate contesting each election at both the state and national levels, along with their political and demographic characteristics. For the purposes of this paper, I collapse the data to the election–constituency level.

To link state assembly constituencies with their corresponding Lok Sabha constituencies, I rely on two official Delimitation Commission reports, one from the 1970s and the other from 2008. Since no clean dataset exists for this mapping, I construct the links manually. Owing to constituency reorganization during the 1990s, it is not possible to establish complete linkages for Delhi and Arunachal Pradesh prior to 2008. For all other states, I construct a complete set of assembly–parliamentary constituency mappings for elections held between 1999 and 2013.

For the measurement of local economic activity, I employ satellite-based night-lights (NL) data collected by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP–OLS), operated by NASA since the 1970s. I use the constituency-level dataset developed by DDL, which maps DMSP–OLS observations to Indian state legislative assembly boundaries. The dataset measures the average annual night-sky brightness for each constituency on a scale ranging from 0 (least bright) to 63 (most bright). Night-light intensity is computed as the total luminosity within constituency boundaries divided by the number of pixels.

Night lights are widely recognized as a proxy for economic activity in contexts where reliable and frequent income or output data are unavailable. In India, night-light intensity correlates approximately 0.6 with wealth and 0.4 with income at the assembly-constituency level (Dhillon et al., 2016). Prior research further validates night lights as a measure of aggregate economic activity (Doll et al., 2006; Henderson et al., 2012; Gibson et al., 2020). Figure 3 shows the night-lights map of India in 1999, the starting year of our study, and 2013, the final year. Over the 14-year period, metropolitan areas appear markedly brighter, and several previously impoverished states such as Bihar exhibit substantial increases in luminosity by 2013.

### 4.2 Descriptive Statistics

While DMSP–OLS constituency-level data are available from 1993 to 2013, I restrict the sample to 1999–2013 due to political instability and frequent parliamentary elections between 1993 and 1999 (three national elections in six years). Collapsing the election data to the assembly level yields 12,431 total assembly elections for this period. The analysis focuses on assembly elections where the political party that won the corresponding parliamentary constituency in the most recent national election appears either as the winner or the runner-up.

Table 1 presents summary statistics for both the full sample of constituencies where the parliamentary constituency's winning party finished in the top two of the assembly election (Panel A) and the subsample of close elections (Panel B, margin $< 5$ percentage points). We separately compare constituencies where the MP and MLA belong to different parties ($NA$, non-alignment) versus the same party ($A$, alignment).

Several differences emerge. In the full sample, aligned constituencies are more likely to have incumbents (37% vs. 29%), slightly more educated legislators (12.0 vs. 11.7 years of schooling), and a markedly higher share of state-government coalition members (72% vs. 49%). Asset holdings are lower in aligned constituencies, though asset differences are not statistically significant in the close-election subsample. Gender and caste composition are similar across groups, with female representation around 7-8% and SC/ST winners around 29–30%. Results are broadly consistent in the close-election sample, though effect sizes are smaller; incumbency and coalition membership remain significantly higher in aligned constituencies. Overall, these descriptive patterns suggest that aligned areas are more politically advantaged through incumbency and coalition participation.

These variables are therefore explored further in the heterogeneity analysis and covariate balance tests.

Some states feature two-party competition, while others have three or more politically salient parties, increasing electoral fragmentation. Table 2 reports, by state, the share of elections in which the parliamentary constituency's winning party finishes in the top two of the related assembly election. Large states like Madhya Pradesh and Gujarat exceed 90%, reflecting dominance by the two major national parties—the BJP and Congress. Figure 6 plots the nationwide share over time, which remains around 70% throughout the period. About 45% of assembly elections in the dataset are won by the same party that won the parliamentary election.

As explained, the main outcome variable is NL growth. Because the data are at the constituency-year level, a single assembly constituency can contribute between zero and four NL growth observations. The full sample comprises 33,421 constituency-year observations in which the parliamentary constituency winner placed in the top two of the assembly election. Figure 3 shows that in this full sample ($N = 33{,}421$), aligned constituencies exhibit an average annual growth of 3.18% versus 3.11% for non-aligned constituencies, a mean difference of $-0.07$ percentage points ($p = 0.83$).

A common challenge with DMSP–OLS data is that very low baseline NL intensities can generate spuriously large growth rates. Figure 7 contrasts the distribution of NL growth for constituencies with baseline NL $< 2$ versus $> 2$: the low-light group has mean growth of $-2.1$, while the higher-light group averages 5.5. Panel B shows how growth stabilizes as baseline NL increases. To avoid low-light artifacts, I restrict the analysis to constituency–years with baseline NL $\geq 2$.

In this restricted sample ($N = 24{,}505$), aligned and non-aligned constituencies have nearly identical average growth (5.50% vs. 5.52%, $p = 0.96$). In the close-election subset (baseline NL $\geq 2$ and assembly margin $< 5\%$, $N = 7{,}172$), the averages are 5.67% (aligned) and 5.97% (non-aligned), a small and statistically insignificant difference ($p = 0.60$). Overall, the descriptive evidence shows no systematic differences in NL growth by MP–MLA alignment.

# 5 Methodology

This paper employs a regression discontinuity (RD) design to estimate the causal effect of MP–MLA party alignment on local development outcomes, namely annual growth in night-lights (NL) intensity and road construction, at the assembly-constituency level. The analysis is restricted to state assembly elections in which either the winning or the runner-up candidate belonged to the same party as the MP from the most recent corresponding Lok Sabha election.

Following Hahn et al. (2001), I estimate a local-linear specification:

$$Y_{c,t+1} = \beta_0 + \beta_1 \, \text{Alignment}_{ct} + \beta_2 \, \text{Margin}_{ct} + \beta_3 \left( \text{Margin}_{ct} \times \text{Alignment}_{ct} \right) + X_{ct} + \varepsilon_{ct}, \quad \forall \, \left| \text{Margin}_{ct} \right| \leq \text{CCT\%} \tag{1}$$

where $Y_{c,t+1}$ denotes the year-on-year change in NL intensity for constituency $c$ in year $t$, computed as the difference in the logarithm of NL intensity between $t$ and $t-1$. The sample includes all years between the alignment election and the subsequent assembly election. $Alignment_{ct}$ equals one if the winning assembly candidate's party matches the MP's party from the most recent Lok Sabha election, and zero otherwise. $Margin_{ct}$ is the vote-share difference between the assembly winner and runner-up, coded positive when the aligned candidate wins and negative otherwise.

Estimation is restricted to observations within a data-driven bandwidth selected using the optimal procedures of Calonico et al. (2014, 2019). I employ a triangular kernel that assigns higher weight to elections with margins closer to zero and zero weight outside the selected bandwidth. This local, nonparametric approach avoids the well-documented pitfalls of global high-order polynomial fits in RD applications (Gelman and Imbens, 2019).

The vector $X_{ct}$ collects three groups of covariates. *First, candidate-level controls*: gender, caste, incumbency status, number of prior candidacies, and an indicator for whether the winner's party belonged to the governing coalition in that election. For the post-2004 subsample, additional candidate attributes—age, education, declared assets, and criminal status—are available; these are excluded from the main specification to preserve sample size but included in robustness analyses. *Second, constituency-level controls*: lagged NL intensity, lagged NL growth, voter turnout, constituency population, and indicators for Scheduled Caste / Scheduled Tribe reservation. These variables absorb residual differences between aligned and non-aligned constituencies, improving precision and the bias–variance tradeoff in bandwidth selection. Additional characteristics (rural share, literacy, broader caste composition) are omitted from the baseline because of substantial missingness but are incorporated in robustness checks. *Third, fixed effects*: year and state fixed effects are added in some specifications to absorb common shocks and to address concerns that aligned parties may be systematically more likely to narrowly win in certain places or periods. Standard errors are clustered at the assembly-constituency level.

The parameter of interest, $\beta_1$, measures the effect of electing an aligned MLA on NL growth and road construction. Identification relies on the quasi-random assignment of winners in close elections: as the victory margin approaches zero, aligned and non-aligned constituencies should be comparable in observed and unobserved determinants of outcomes. Under this assumption, the discontinuity in outcomes at the cutoff recovers the local average treatment effect of alignment.

Since the credibility of the RD estimate hinges on the running-function correctly approximating NL growth on either side of the cutoff, I implement two complementary sets of specification checks. *First, bandwidth sensitivity.* I use two optimal bandwidth selectors—the mean squared error (MSE) and coverage error rate (CER) criteria of Calonico et al. (2014, 2019)—to vary the window over which the local kernel regression is fit. Both procedures balance larger-bandwidth bias (from poorer functional-form fit) against the precision gains from a larger effective sample. The MSE selector minimizes the sum of squared bias and variance of the RD estimator, whereas CER minimizes the confidence-interval coverage error; the CER bandwidth is therefore typically narrower than the MSE bandwidth. *Second, alternative running-variable specifications.* I re-estimate the model using a quadratic function of the margin, and also under a restricted specification that imposes a zero slope on the margin term. In addition, independently of specification, I estimate using the full sample and compare to results obtained after trimming the most extreme 5% of NL-growth observations, to assess sensitivity to tail behavior in the outcome distribution.

Under the close-election random-assignment assumption, $\beta_1$ identifies the causal effect of MP–MLA alignment on NL growth. However, as in any RD design, this interpretation presumes there are no discontinuous shifts at the cutoff in other politician characteristics that themselves affect outcomes. Aligned and non-aligned candidates contesting tight races could differ systematically in ways that matter for development. To probe this, I conduct continuity tests for observable covariates at the threshold and re-estimate the main models including the candidate- and constituency-level controls described above. While unobservables (e.g., candidate ability) could in principle vary discontinuously at the cutoff, incorporating rich observed controls narrows the scope for such bias and bolsters the interpretation of $\beta_1$ as the causal effect of alignment on NL intensity growth and road building.

# 6 Results

In this section, I present the main regression discontinuity (RD) estimates of the effect of MP–MLA alignment on local development outcomes. I begin with the baseline RD estimates for night-lights growth and road construction. I then assess the credibility of the identification strategy using continuity and placebo checks. Next, I evaluate robustness by varying the bandwidth and functional form of the running variable, trimming extreme observations, and incorporating additional covariates. Finally, I explore heterogeneity across different institutional and political contexts.

## 6.1 Main RD Estimates

We begin by presenting the regression discontinuity (RD) effect of electing an MLA aligned with the MP's party on yearly growth in night-time lights. Figure 8 plots NL growth against the margin of victory for an election in percentage points, where positive margins indicate a win by the aligned party and negative margins indicate a loss. To construct the figure, I use a binning strategy with two bins per percentage point of margin of victory. Each marker represents the average NL growth in that bin, and the solid lines represent local-linear fits on either side of the cutoff, estimated with a triangular kernel and the optimal bandwidth procedure. Observations are restricted to constituency-years where the minimum night-light intensity in the constituency is at least 2, in order to mitigate the influence of extremely noisy values from dimly lit constituencies.

The plot shows no visible discontinuity at the cutoff, which signifies that constituencies narrowly won by aligned candidates do not exhibit systematically higher NL growth than those narrowly lost. This impression is confirmed by the formal RD estimates in Table 4. Using the CER bandwidth (column 1), the estimated effect of alignment is 0.080 (SE = 0.92), while the MSE bandwidth (column 2) which corresponds to the bandwidth used for the RD plot yields an estimate of –0.0046 (SE = 0.77). Across alternative specifications, including a fixed $\pm 5$ percentage-point window (column 3) and halved versions of the CER and MSE bandwidths (columns 4 and 5), the estimated effects remain small in magnitude and statistically insignificant, with the estimate ranging from -0.0046 to 1.02 percentage points overall through the 5 bandwidth specifications I use.

Given that our RD estimates are extremely small, it is useful to benchmark their magnitude against related studies. Our estimated effect of MP–MLA alignment on night-lights growth is close to zero and, in absolute terms, much smaller than effects typically reported for other political margins in India. For example, Asher and Novosad (2017) report alignment of MLA with the state ruling party to have an effect on the order of $\sim$4 percentage points (pp), while Prakash (2019) find that electing a criminally accused politician reduces outcomes by roughly $\sim$25 pp; Baskaran et al. (2024) estimate gains of about $\sim$15 pp for female politicians; and defection-driven alignment effects are around $\sim$4.4 pp (Makkar, 2023). In contrast, our RD point estimates are near zero (roughly 0.0 to 1.0 pp) and statistically indistinguishable from zero, indicating to tghe likelihood that the vertical political alignment of MP and MLA does not significantly impact local area development.

### 6.2 Identification and Placebo Tests

A key assumption of the RD framework is that the assignment of aligned and non-aligned MLAs in very close elections is quasi-random. This requires two conditions: (i) that candidates cannot precisely manipulate the margin of victory at the cutoff, and (ii) that observable constituency and candidate characteristics evolve smoothly across the cutoff.

To test the first condition, I conduct a McCrary (2008) density test for manipulation of the running variable. Figure 9 plots the density of elections by margin of victory, with local polynomial fits estimated on either side of the cutoff. The estimated discontinuity at zero is statistically indistinguishable from zero (p=0.41), indicating no evidence of aligned candidates systematically manipulating close election outcomes.

A historical concern in the Indian context is "booth capturing" and related forms of electoral malpractice, which could, in principle, distort the distribution of close races. However, a series of institutional reforms—most notably stricter enforcement by the Election Commission under T. N. Seshan in the 1990s, followed by the rollout of electronic voting machines (and later VVPATs), tighter security deployments, and improved rolls—substantially curtailed scope for such manipulation. While these reforms reduce ex ante concerns about manipulation near the cutoff, I still implement the density test as a falsification check and the absence of a discontinuity supports the RD design's validity in this setting.

The key identifying assumption of the RD design is that, absent alignment, potential outcomes would evolve smoothly through the cutoff. In practice, this requires that aligned and non-aligned constituencies be comparable on predetermined characteristics. While the McCrary density test (Figure 9) rules out manipulation of the running variable, I further probe validity by testing for discontinuities in observable covariates at the cutoff.

Table 8 reports RD estimates on constituency-level covariates and Table 9 examines candidate-level covariates, including gender, caste, education, wealth, incumbency, criminal charges, and age. Most estimates are small and statistically indistinguishable from zero except for two candidate level characteristics thatshow weak evidence of discontinuity: aligned winners are about 3 percentage points more likely to be female ($p < 0.05$) and about 7 percentage points more likely to be incumbents ($p < 0.01$). Given the number of tests conducted, these isolated results may arise by chance, and in any case the magnitudes are modest relative to overall variation. While the identifying assumption implies that no predetermined covariates should exhibit discontinuities at the cutoff, conducting multiple balance tests increases the likelihood of detecting spurious differences. In our case, two out of sixteen estimates are statistically significant (about 12.5%), which is somewhat higher than the 5% that would be expected by chance at the conventional significance level. However, the main RD estimates of alignment on NL growth are robust to controlling directly for these characteristics (see Table 5), which mitigates concerns that they bias the treatment effect.

### 6.3 Robustness Analyses

Table 4 shows that the baseline RD estimates are consistently small and statistically insignificant across a range of bandwidth choices and polynomial specifications. To further assess robustness, I extend the analysis by sequentially adding a rich set of controls, restricting the sample more stringently, and considering alternative functional forms.

Table 5 reports estimates where columns (1)–(5) use the CER bandwidth and columns (6)–(10) use the MSE bandwidth. Within each bandwidth choice, I progressively incorporate candidate-level controls (winner gender, caste, incumbency, prior candidacies, coalition status), constituency-level controls (lagged night-lights level and growth, turnout, population, reservation status), and year and state fixed effects. Across all ten specifications, the estimated coefficients on alignment remain small in magnitude, alternating between slightly positive and slightly negative, and never statistically different from zero. For instance, under the CER bandwidth, estimates range from 0.08 in column (1) to $-0.69$ in column (5), while under the MSE bandwidth they vary between $-0.0046$ and $-0.74$. In all cases, the robust standard errors exceed the point estimates, leaving coefficients imprecisely estimated and close to zero.

As an additional robustness filter, I restrict the sample to constituencies that maintain a night-lights intensity of at least 2 throughout the entire MP–MLA overlap period, rather than meeting this criterion year by year. This stricter condition ensures that temporary dips in night-lights do not influence the analysis. The results, reported in Table 6, are again unchanged: alignment effects remain near zero and statistically insignificant across specifications. Under the CER bandwidth (columns 1–5), RD estimates range from $-0.29$ to 0.45; under the MSE bandwidth (columns 6–10), they range from $-0.21$ to 0.66. In all cases, estimates remain imprecisely estimated and statistically indistinguishable from zero.

Taken together, the stability of the estimates to extensive control sets and stricter sample definitions reinforces the baseline conclusion: electing an aligned MLA has no systematic effect on subsequent night-lights growth. If anything, adding controls modestly decreases the standard errors, indicating that the null result is unlikely to reflect omitted-variable bias, imbalances in predetermined covariates, or composition at the lower end of the night-lights distribution.

Table 7 and Figure 14 report local *quadratic* RD estimates using five bandwidth choices (CER, CER/2, MSE, MSE/2, and a symmetric $\pm 5$ pp window), with no additional controls or fixed effects. Point estimates range from 0.39 to 1.35 percentage points, while clustered standard errors lie between 1.43 and 2.66, leaving all estimates statistically indistinguishable from zero. The visual fit in Figure 14 similarly shows no salient kink at the cutoff. These results mirror the linear specifications and indicate that the null finding is not driven by functional-form or bandwidth choice; consistent with best practice, I treat the quadratic fit as a sensitivity check, with the local linear, data-driven bandwidth estimates as the baseline.

## 6.4 Heterogeneity

While the average effect of MP–MLA alignment on local development is small and statistically indistinguishable from zero, the impact may not be uniform across contexts. Political economy arguments suggest that alignment could matter more where state capacity is weaker (and coordination can relax binding administrative constraints), where candidate incentives differ, or where the duration of overlap shapes the ability to deliver tangible projects. I therefore examine heterogeneity along three dimensions: *state characteristics*, *candidate traits*, and the *length of MP-MLA overlap*.

### 6.4.1 State characteristics

India's federal system encompasses states with vastly different developmental baselines, institutional capacity, and governance quality. Exploring heterogeneity along these dimensions is important because the returns to vertical political alignment may depend on whether partisan coordination relaxes binding administrative constraints. In weaker states, alignment could help overcome bottlenecks in project execution, whereas in richer or more institutionalized states, bureaucratic systems may deliver services irrespective of partisan congruence.

To capture this variation, I classify states along several axes. First, I consider the group of so-called BIMAROU states (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh), which historically have lagged behind in social and economic development and are often cited as exhibiting weaker governance structures. Second, I examine "least developed" states as identified by national planning documents, which face chronic capacity constraints and underinvestment in infrastructure. Third, I look at states characterized by relatively high levels of corruption, where political connections could plausibly shape access to funds or administrative clearances. Finally, I contrast these with "rich" states, which enjoy stronger economic bases, higher revenues, and more institutionalized bureaucracies.

Table 10 reports RD estimates by state type. Alignment is statistically significant only in least developed states, where aligned constituencies show 2.9–4.6 percentage points higher night-lights growth across bandwidths. Estimates for BIMAROU, high-corruption, and rich states are negative or near zero and never significant. Because this stratification reduces sample size, I probe whether the least-developed result survives richer specification controls.

Table 11 presents least-developed–state estimates with progressively added controls. Under CER bandwidths (cols. 1–4), the point estimate falls from $3.56^{**}$ (no controls) to 2.38 with candidate controls, 3.16 with constituency controls, and essentially zero ($-0.12$) once candidate *and* constituency controls plus fixed effects are included; none of these controlled specifications are statistically significant given robust standard errors of 2.39–4.16. A similar pattern holds under MSE bandwidths (cols. 5–8): the estimate declines from $2.89^{**}$ (no controls) to 1.75 with candidate controls, 1.84 with constituency controls, and $-0.20$ with the full set of controls and fixed effects.

Overall, once observable differences are accounted for, the initially positive effect in least developed states attenuates toward zero and loses statistical significance. This indicates that the earlier significance is not robust to the inclusion of candidate- and constituency-level controls and fixed effects.

#### 6.4.2 Candidate characteristics

Alignment may also depend on who the MLA is. If the MLA's party controls the state government, aligned legislators may have better access to funds and clearances; education and incumbency could likewise influence how effectively alignment is leveraged. Table 12 splits the sample by ruling status, education, and incumbency. Estimates for ruling-party MLAs are positive but imprecise, while those for non-ruling MLAs are negative and imprecise. Education-based splits yield small, null effects for both college-educated and less-educated MLAs. By contrast, the incumbency split shows a notable asymmetry: alignment with *non-incumbent* MLAs produces positive (though insignificant) coefficients, whereas alignment with *incumbents* is consistently negative and insignificant. This is consistent with the idea that alignment may matter more for new legislators seeking to establish networks, while incumbents may already possess relationships that attenuate the marginal value of alignment.

#### 6.4.3 Years of overlap

An additional dimension of heterogeneity is the length of time MPs and MLAs remain aligned. Longer overlap could plausibly deepen coordination, as legislators build relationships and align agendas, or, alternatively, any advantages could be front-loaded—such as expedited clearances or early project signaling—without compounding over time. Examining this distinction helps clarify whether alignment generates durable institutional effects or merely short-term administrative gains.

Table 13 reports estimates for constituencies with one to two years of overlap (Panel A) versus three to four years of overlap (Panel B). For shorter overlaps, coefficients are consistently positive across bandwidths, ranging from 1.2 to 3.7 percentage points, though none are statistically significant given the imprecision of the estimates. By contrast, for longer overlaps, coefficients turn negative (between -0.66 and -1.25) and remain insignificant.

Taken together, the patterns by overlap length indicate that alignment yields its largest (albeit imprecise) gains when elections are nearer. For constituencies with one to two years of overlap, coefficients are uniformly positive across bandwidths (1.2-–3.7 p.p.), whereas with three to four years of overlap the yearly NL growth turns small and negative. This suggests that alignment effects, if present, are concentrated in the run-up to elections which would again lead to accelerated clearances or visible project delivery under shorter electoral horizons rather than accumulating steadily with tenure.

## 7 Public Goods

While night-lights provide a useful proxy for overall economic activity, they do not capture the distribution of specific public goods that directly affect household welfare. Roads are particularly important in this respect, as they enhance access to markets, schools, and health services, and often represent one of the most visible forms of government investment in rural areas. Studying roads as an outcome therefore allows us to complement the night lights analysis with a measure that is both concrete and citizen facing. Despite the centrality of road construction in India's development strategy through flagship programs such as the Pradhan Mantri Gram Sadak Yojana, the role of vertical political alignment of MP and MLA in shaping road provision has been largely overlooked. By incorporating roads alongside night lights, this paper provides new evidence on whether partisan coordination across tiers of government translates into tangible infrastructure improvements.

Table 14 reports the RD estimates of MP-MLA alignment on road provision. Across bandwidth choices, the coefficients vary in sign and magnitude, ranging from -0.38 to 6.60 percentage points, with standard errors between 5 and 7 points. None of the estimates are statistically significant, and the wide confidence intervals reflect the very limited number of observations near the cutoff (fewer than 200 constituencies on each side in most specifications). With such a small sample, it is difficult to draw firm conclusions about whether alignment systematically affects road construction. Nonetheless, the point estimates are generally positive, which is consistent with the possibility that alignment may facilitate some additional road building, though the evidence remains too imprecise to be conclusive. Figure 15 depicts the RD estimate when using MSE bandwidth algorithm.

## 8 Conclusion

Most voters in India cast their ballots with the hope of securing a better tomorrow, electing politicians whom they believe can improve their lives. Yet citizens are often in the dark about how institutional and political arrangements shape the actual delivery of development. The recent rhetoric of "double engine" governance exemplifies this gap, encouraging voters to expect stronger outcomes when the MP and MLA belong to the same party. This paper provides the first evidence that such vertical alignment does not translate into measurable gains in aggregate economic output, as proxied by night-lights and road provision. The results suggest that partisan coordination across tiers may matter less than commonly assumed, at least for broad development indicators.

Looking ahead, future work could explore whether alignment influences other domains of governance, such as the targeting of welfare schemes, the speed of project approvals, or the distribution of political rents. It will also be important to examine whether alignment effects emerge in more localized or sectoral outcomes, even if not visible in aggregate growth. By clarifying what alignment does and does not deliver, this study contributes to a more nuanced understanding of political accountability in federal systems and can help inform both voters' expectations and policy debates on intergovernmental coordination.

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# 9 Tables and Graphs


Figure 1: Map of Parliamentary Constituencies in India

*Notes:* The figure shows the 543 Lok Sabha constituencies used in the analysis, each electing one Member of Parliament under a first-past-the-post system. *Source:* India GIS Database (Lok Sabha constituency shapefile, Election Commission of India).


Figure 2: Map of State Legislative Assembly Constituencies in India

*Notes:* The figure shows all state legislative assembly constituencies (Vidhan Sabha seats) used in the analysis, each electing one Member of the Legislative Assembly under a first-past-the-post system. *Source:* India GIS Database (state legislative assembly constituency shapefiles, Election Commission of India).

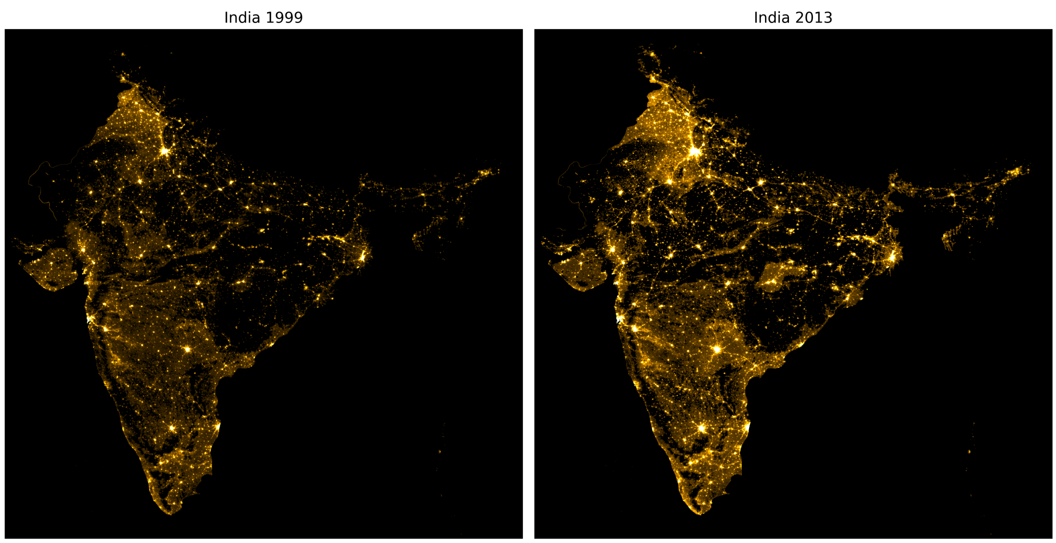


Figure 3: India at Night, 1999 vs. 2013

*Notes:* The panels show satellite-derived night-time lights for India in 1999 (left) and 2013 (right), illustrating the increase in luminosity over the study period, especially around major metropolitan areas and previously low-light regions. *Source:* DMSP–OLS night-time lights data.

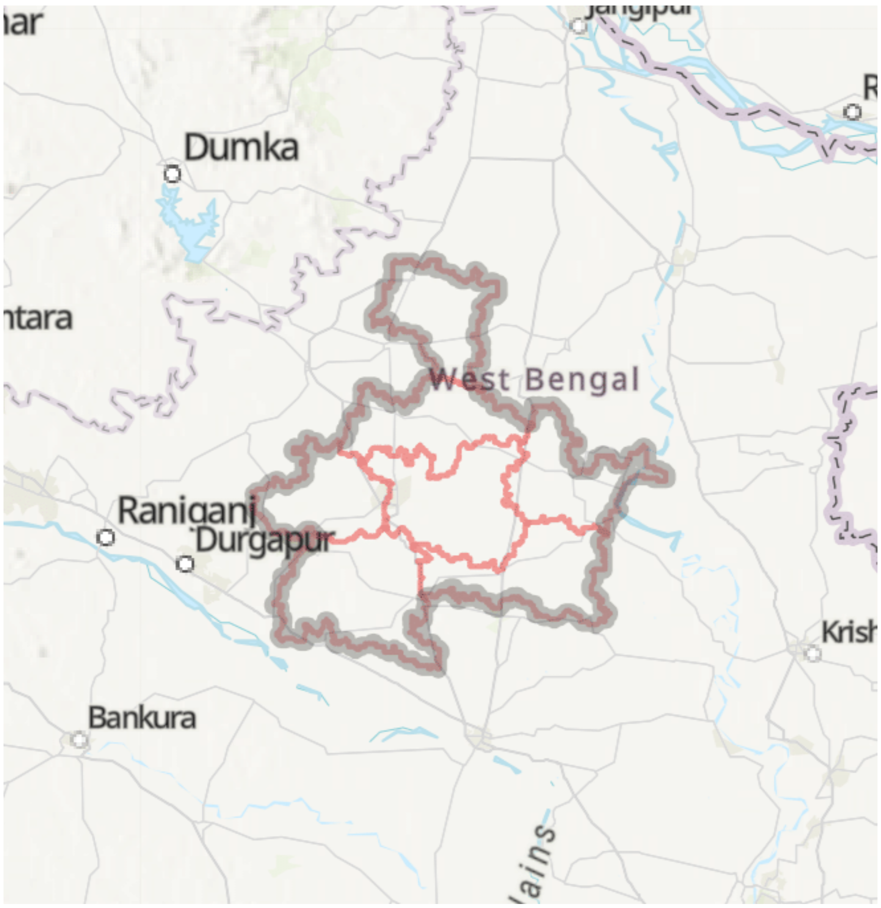


Figure 4: Parliamentary–State Assembly Mapping

*Notes:* The figure shows the Bolpur parliamentary constituency in West Bengal and its seven nested state assembly segments, illustrating how multiple assembly constituencies are encapsulated within a parliamentary constituency. *Source:* India GIS Database (parliamentary and assembly constituency shapefiles, Election Commission of India).

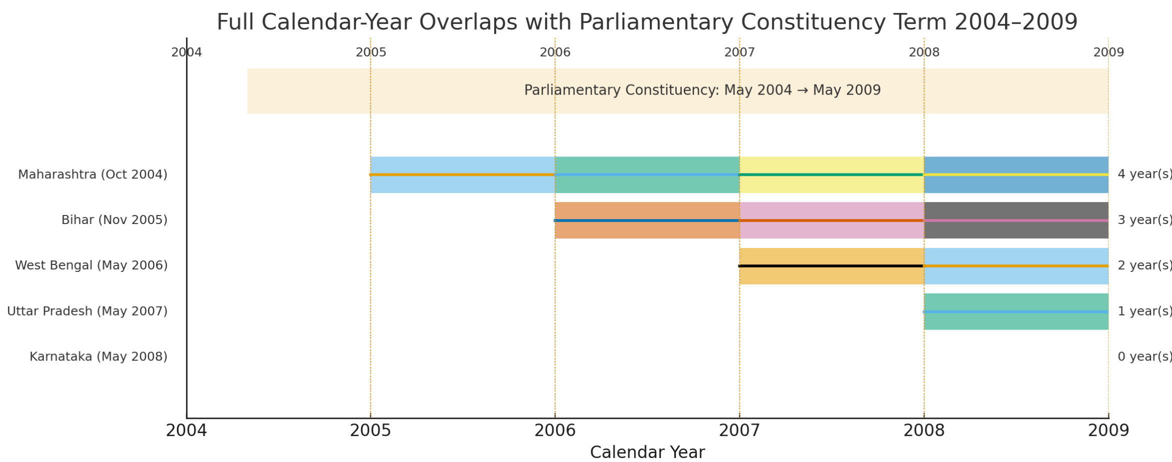


Figure 5: Alignment Formation Explanation

*Notes:* The figure illustrates how overlaps between national (parliamentary) and state (assembly) election cycles generate varying durations of MP–MLA political alignment across constituencies. The highlighted segments show examples of full and partial overlaps used to define clean alignment years in the analysis.

Table 1: Summary Statistics: Full Sample and Close-Election Subsample

**Panel A: Summary Statistics – Full Sample**

| | Total Obs | NA Mean | A Mean | NA - A | P-value |
|---|---|---|---|---|---|
| Age | 5593 | 49.98 | 50.48 | -0.50 | 0.08 |
| Female | 9412 | 0.07 | 0.08 | -0.01 | 0.08 |
| SC/ST | 5589 | 0.29 | 0.30 | -0.02 | 0.17 |
| Total Assets (Rupees) | 4579 | 42749775.27 | 30047051.73 | 12702723.55 | 0.02 |
| Asset Growth (%) | 2063 | 1.08 | 1.13 | -0.05 | 0.46 |
| Charged with Major Crime | 4480 | 0.13 | 0.13 | 0.00 | 0.96 |
| Incumbent | 9519 | 0.29 | 0.37 | -0.09 | 0.00 |
| Years of Education | 4418 | 11.72 | 12.04 | -0.31 | 0.00 |
| Governing Coalition Member? | 9477 | 0.49 | 0.72 | -0.24 | 0.00 |
| Number of Elections | 9519 | 2.57 | 2.56 | 0.01 | 0.80 |

**Panel B: Summary Statistics – Close Elections (MLA Level)**

| | Total Obs | NA Mean | A Mean | NA - A | P-value |
|---|---|---|---|---|---|
| Age | 1746 | 50.14 | 50.25 | -0.10 | 0.84 |
| Female | 2827 | 0.06 | 0.08 | -0.02 | 0.07 |
| SC/ST | 1747 | 0.28 | 0.30 | -0.02 | 0.32 |
| Total Assets (Rupees) | 1477 | 21892745.22 | 24851578.57 | -2958833.35 | 0.42 |
| Asset Growth (%) | 639 | 1.06 | 1.16 | -0.10 | 0.30 |
| Charged with Major Crime | 1444 | 0.12 | 0.13 | -0.01 | 0.58 |
| Incumbent | 2852 | 0.28 | 0.34 | -0.06 | 0.00 |
| Years of Education | 1418 | 11.60 | 12.11 | -0.51 | 0.00 |
| Governing Coalition Member? | 2842 | 0.38 | 0.62 | -0.24 | 0.00 |
| Number of Elections | 2852 | 2.52 | 2.50 | 0.01 | 0.84 |

*Notes:* Panel A reports descriptive statistics for the full sample of constituencies in which the parliamentary constituency's winning party finishes in the top two of the corresponding assembly election. Panel B restricts to the close-election sample at the MLA level (assembly margin $<$ 5 percentage points).

Table 2: Central Party Presence in State Elections

| State | PC Winner in Top 2 | PC Party Wins |
|---|---|---|
| Andhra Pradesh | 0.79 | 0.55 |
| Arunachal Pradesh | 0.96 | 0.68 |
| Assam | 0.70 | 0.43 |
| Bihar | 0.55 | 0.31 |
| Chhattisgarh | 0.59 | 0.37 |
| Delhi | 0.45 | 0.24 |
| Goa | 0.75 | 0.37 |
| Gujarat | 0.97 | 0.56 |
| Haryana | 0.73 | 0.48 |
| Himachal Pradesh | 0.80 | 0.35 |
| Jammu & Kashmir | 0.54 | 0.25 |
| Jharkhand | 0.49 | 0.25 |
| Karnataka | 0.69 | 0.43 |
| Kerala | 0.56 | 0.39 |
| Madhya Pradesh | 0.90 | 0.53 |
| Maharashtra | 0.59 | 0.37 |
| Manipur | 0.63 | 0.43 |
| Meghalaya | 0.67 | 0.40 |
| Mizoram | 0.58 | 0.33 |
| Nagaland | 0.83 | 0.49 |
| Odisha | 0.72 | 0.51 |
| Puducherry | 0.38 | 0.23 |
| Punjab | 0.80 | 0.43 |
| Rajasthan | 0.83 | 0.34 |
| Sikkim | 0.98 | 0.90 |
| Tamil Nadu | 0.47 | 0.27 |
| Tripura | 0.92 | 0.77 |
| Uttar Pradesh | 0.62 | 0.32 |
| Uttarakhand | 0.57 | 0.33 |
| West Bengal | 0.73 | 0.53 |

*Notes:* The table reports, by state, the share of elections from 1999–2013 in which the party that won the parliamentary constituency (PC) (i) finished in the top two in the corresponding state assembly election and (ii) won the assembly seat.

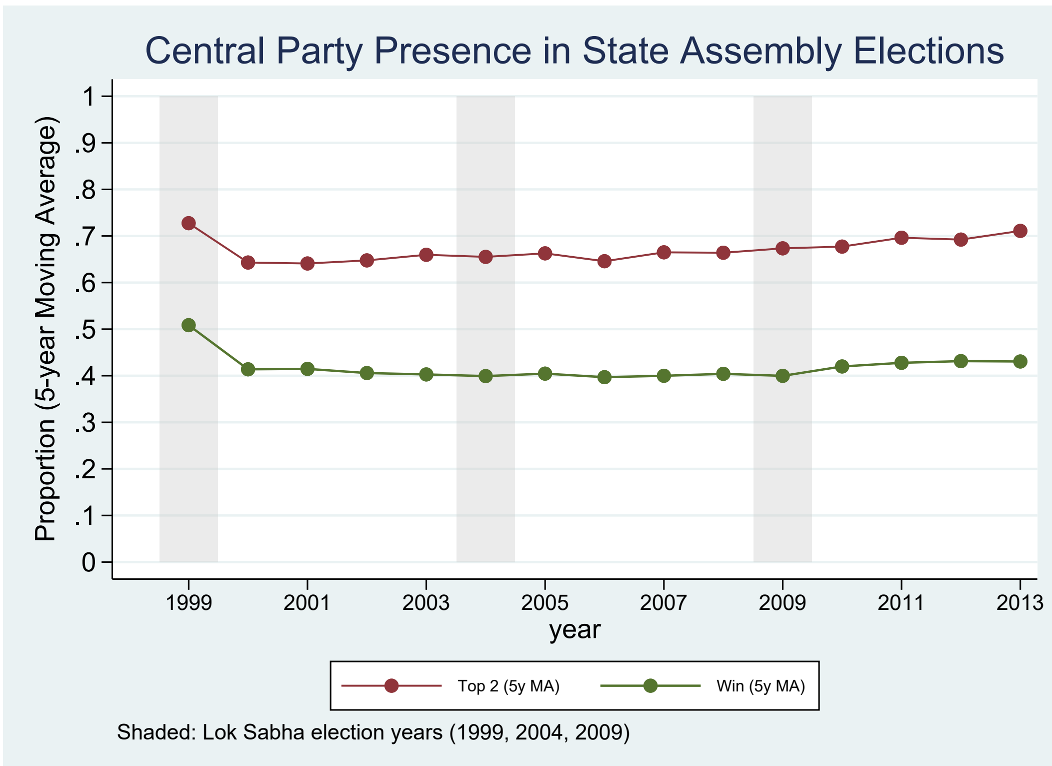


Figure 6: Countrywide Parliamentary Constituency Party Share in State Assembly Elections

*Notes:* The figure plots five-year moving averages of the countrywide share of elections in which the party that won the parliamentary constituency (PC) (i) finished in the top two in the corresponding state assembly election and (ii) won the assembly seat.

Table 3: Annual NL Growth: Non-Aligned vs Aligned Constituencies

| | Obs | Non-Alignment | Alignment | Difference | P-value |
|---|---|---|---|---|---|
| Full Sample | 33421 | 3.11 | 3.18 | -0.07 | 0.83 |
| NL $\geq$2 | 24505 | 5.52 | 5.50 | 0.01 | 0.96 |
| NL $\geq$2 & $<$5% margin | 7172 | 5.97 | 5.67 | 0.29 | 0.60 |
| Observations | 33421 | | | | |

*Notes:* The sample is restricted to elections in which the parliamentary constituency (PC) winning party finished in the top two positions in the corresponding assembly constituency election during our study period, 1999–2013. Each observation represents a constituency–year pair, and the outcome variable measures annual growth in night-lights intensity.

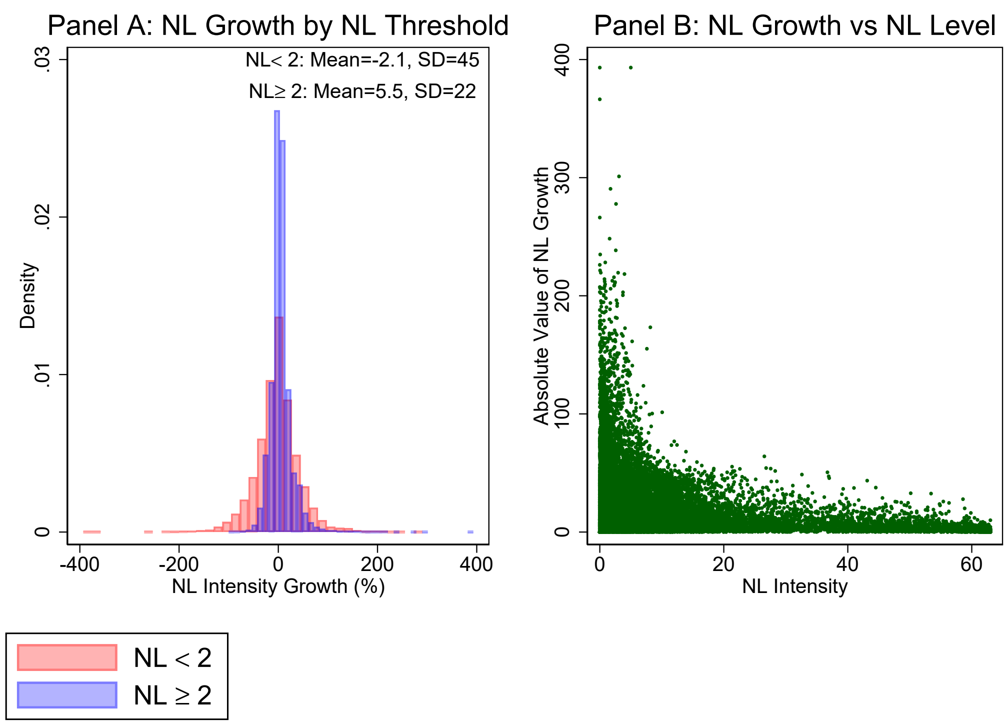


Figure 7: Relationship Between Night-Lights Levels and Growth

*Notes:* The sample is restricted to constituency–years in which the party that won the corresponding parliamentary constituency (PC) finished in the top two positions in the related state assembly election. Each observation in Panel B represents a constituency–year pair. Night-lights (NL) growth in year $t$ is defined as the log difference in NL intensity between years $t$ and $t-1$.

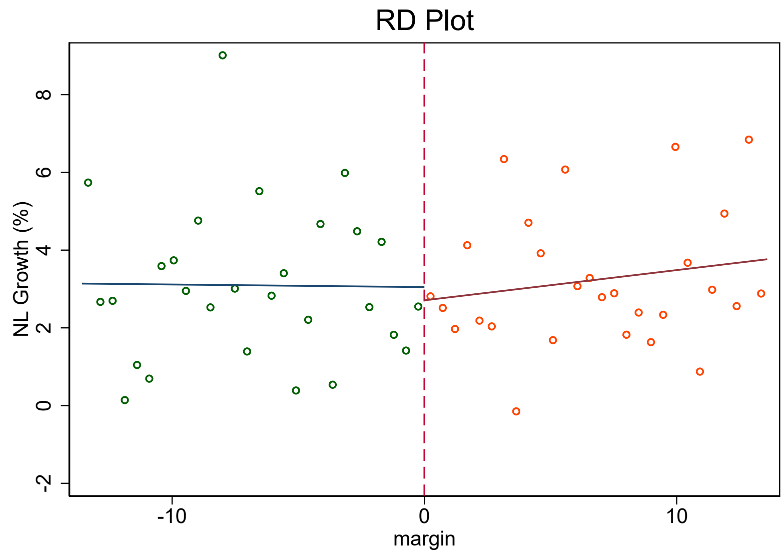


Figure 8: Effect of Political Alignment on Night-Lights Growth

*Notes:* The $x$-axis is the victory margin between the top two candidates in percentage points. Positive values indicate alignment. The plot uses 2 bins per percentage point of margin of victory for binning; lines are local linear fits on each side of the cutoff. Sample restricted to constituency-years with minimum night-lights $\geq 2$; bandwidth chosen by the MSE rule.

Table 4: Main RD estimates with varying bandwidths

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| RD_Estimate | 0.080 | -0.0046 | 0.73 | 0.039 | 1.02 |
| | (0.92) | (0.77) | (1.22) | (1.04) | (1.30) |
| Bandwidth Algorithm | CER | MSE | ±5pp | 0.5 × MSE | 0.5 × CER |
| Bandwidth (pp) | 8.89 | 13.6 | 5 | 6.80 | 4.44 |
| Obs Left | 2237 | 2918 | 1439 | 1853 | 1289 |
| Obs Right | 3033 | 4340 | 1787 | 2390 | 1575 |
| Robust Standard Error | 1.36 | 1.10 | 1.87 | 1.58 | 2.01 |

*Notes:* Each column reports a separate local linear RD estimate of the effect of MP–MLA vertical alignment on night-lights growth with **no controls or fixed effects**. The running variable is the MLA margin of victory (percentage points), and the treatment is party alignment with the constituency's MP. All specifications use a local linear polynomial on each side of the cutoff. Standard errors are clustered at the election level.

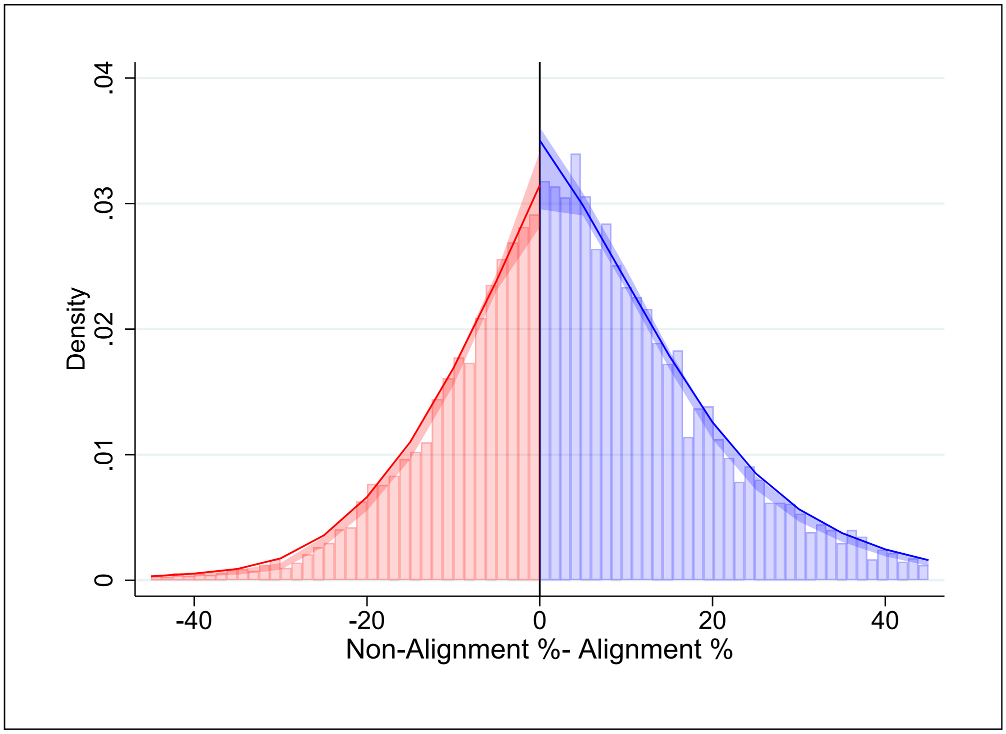


Figure 9: McCrary density test at the alignment cutoff

*Notes:* The $x$-axis plots the margin of victory in percentage points, measured as the difference in vote shares between the top two candidates. Negative values correspond to constituencies without MP–MLA alignment, while positive values correspond to aligned constituencies. The $y$-axis shows the density of elections by margin intervals. The fitted curves on either side of the cutoff are local polynomial estimates of the density function. The estimated discontinuity at the cutoff is small and statistically indistinguishable from zero ($p = 0.41$).

Table 5: RD estimates with linear specification (p=1), CER and MSE bandwidths

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| RD_Estimate | 0.080 | -0.13 | -0.46 | -0.037 | -0.69 | -0.0046 | -0.19 | -0.59 | -0.0023 | -0.74 |
| | (0.92) | (0.91) | (0.68) | (1.16) | (0.81) | (0.77) | (0.76) | (0.57) | (0.93) | (0.64) |
| Bandwidth Algorithm | CER | CER | CER | CER | CER | MSE | MSE | MSE | MSE | MSE |
| Bandwidth (%) | 8.89 | 8.89 | 8.89 | 8.89 | 8.89 | 13.6 | 13.6 | 13.6 | 13.6 | 13.6 |
| Obs Left | 2237 | 2203 | 2203 | 1327 | 1327 | 2918 | 2871 | 2871 | 1743 | 1743 |
| Obs Right | 3033 | 3012 | 3012 | 1973 | 1973 | 4340 | 4310 | 4310 | 2896 | 2896 |
| Robust Standard Error | 1.36 | 1.35 | 1.00 | 1.80 | 1.26 | 1.10 | 1.09 | 0.81 | 1.42 | 0.99 |
| Candidate Controls | N | Y | Y | Y | Y | N | Y | Y | Y | Y |
| Constituency Controls | N | N | N | Y | Y | N | N | N | Y | Y |
| FE | N | N | Y | N | Y | N | N | Y | N | Y |

*Notes:* Reported coefficients correspond to $\beta_1$ from Equation 1.
Equation 1 specifies a local regression discontinuity design using the margin of victory as the running variable, with slopes allowed to differ on either side of the cutoff. Bandwidths are chosen via optimal selection rules (CER or MSE). "Obs Left" and "Obs Right" denote the number of observations where we have non-alignment and alignment, respectively. A first-order polynomial is used. Standard errors (in parentheses) are clustered at the election level. Sample restricted to constituency-years with minimum night-lights $\geq 2$.

Table 6: RD estimates with linear specification (p=1), CER and MSE bandwidths

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| RD_Estimate | 0.43 | 0.23 | -0.12 | 0.45 | -0.29 | 0.54 | 0.40 | -0.070 | 0.66 | -0.21 |
| | (0.88) | (0.87) | (0.59) | (1.09) | (0.70) | (0.72) | (0.72) | (0.49) | (0.88) | (0.56) |
| Bandwidth Algorithm | CER | CER | CER | CER | CER | MSE | MSE | MSE | MSE | MSE |
| Bandwidth (%) | 8.38 | 8.38 | 8.38 | 8.38 | 8.38 | 12.8 | 12.8 | 12.8 | 12.8 | 12.8 |
| Obs Left | 2004 | 1971 | 1971 | 1170 | 1170 | 2666 | 2624 | 2624 | 1563 | 1563 |
| Obs Right | 2703 | 2688 | 2688 | 1765 | 1765 | 3851 | 3830 | 3830 | 2585 | 2585 |
| Robust Standard Error | 1.30 | 1.29 | 0.86 | 1.66 | 1.08 | 1.06 | 1.05 | 0.70 | 1.32 | 0.85 |
| Candidate Controls | N | Y | Y | Y | Y | N | Y | Y | Y | Y |
| Constituency Controls | N | N | N | Y | Y | N | N | N | Y | Y |
| FE | N | N | Y | N | Y | N | N | Y | N | Y |

*Notes:* Coefficients correspond to $\beta_1$ from Equation (1). Equation (1) implements a local RD framework with the MLA's margin of victory as the forcing variable, allowing different slopes on each side of the cutoff. Bandwidths are set by the CER and MSE algorithms. "Obs Left" and "Obs Right" indicate the counts of constituencies where we have non-alignment and alignment, respectively. A linear (order 1) polynomial is applied. Standard errors (in parentheses) are clustered at the election level. Sample restricted to constituencies with minimum night-lights $\geq 2$ throughout the overlappping period.

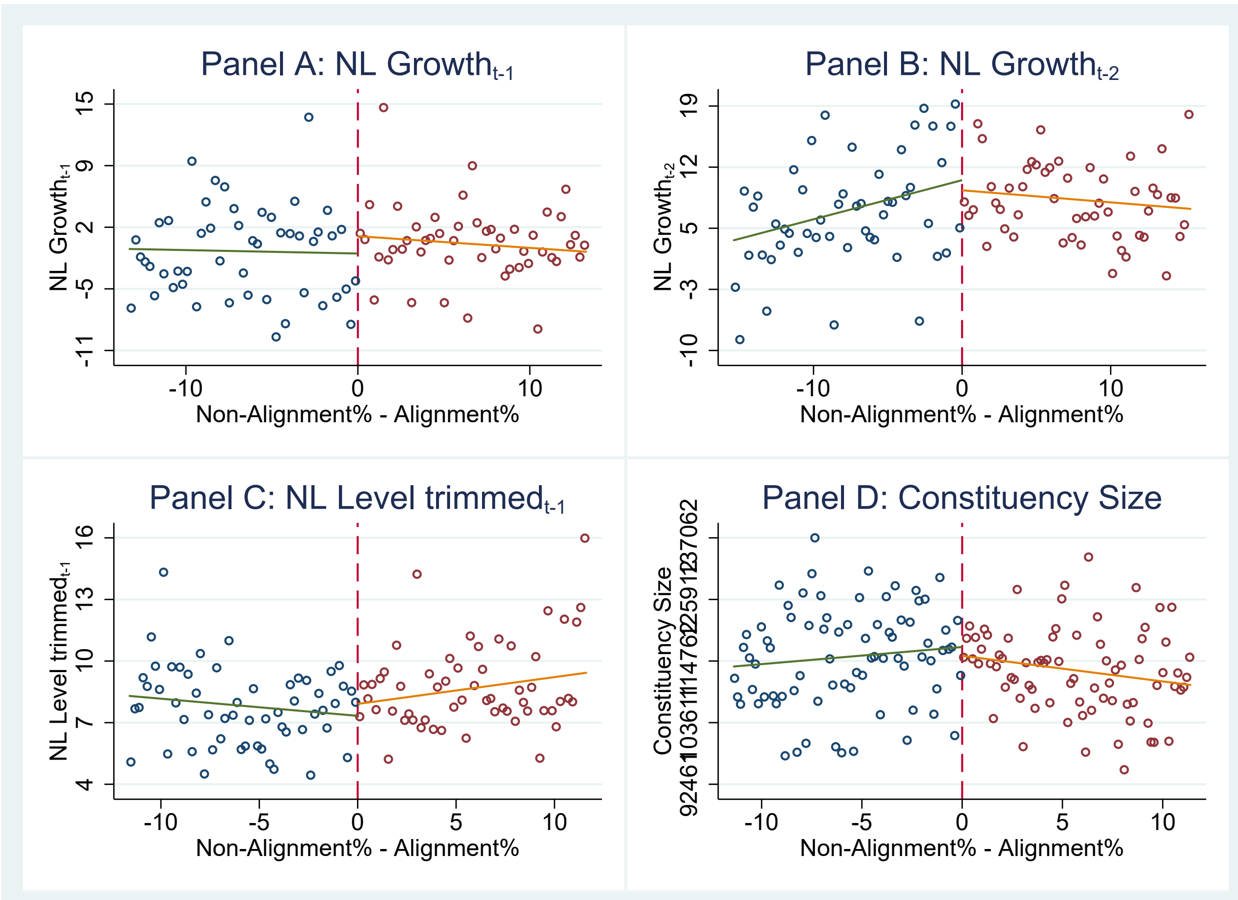


Figure 10: RD plots for constituency-level covariates

*Notes:* The covariates include lagged NL growth ($t-1$, $t-2$), lagged NL level ($t-1$), and constituency size. The $x$-axis shows the vote-share difference between the top two candidates; positive values correspond to alignment, and negative values to non-alignment wins. Each dot represents the average outcome within a margin-of-victory bin, with bin sizes chosen by the mimicking-variance algorithm. Separate local linear fits are plotted on either side of the cutoff, using the MSE bandwidth selector with triangular kernel weights.

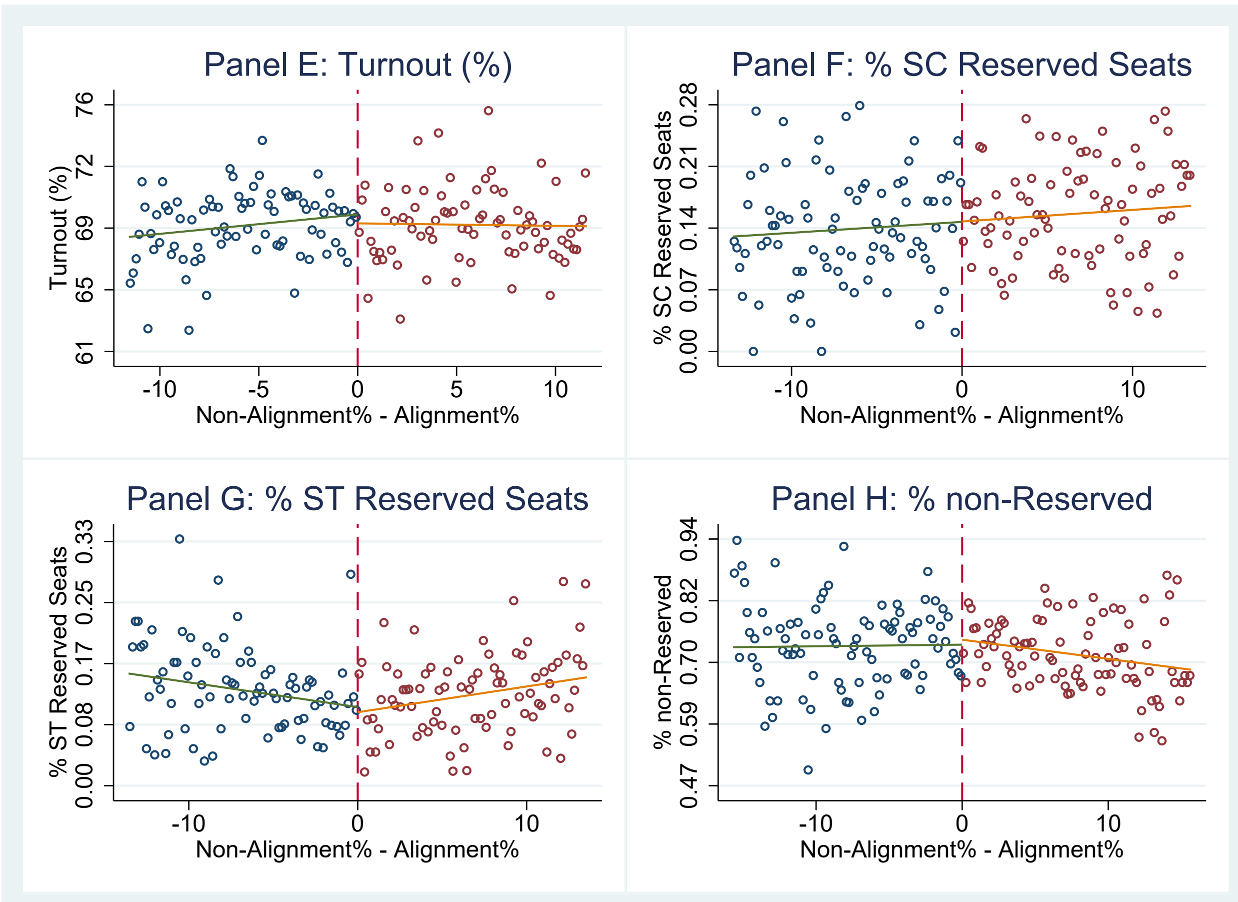


Figure 11: RD plots for constituency-level covariates

*Notes:* The covariates include SC-reserved, ST-reserved, and non-reserved constituencies. The $x$-axis shows the vote-share difference between the top two candidates; positive values correspond to alignment, and negative values to non-alignment wins. Each dot represents the average outcome within a margin-of-victory bin, with bin sizes chosen by the mimicking-variance algorithm. Separate local linear fits are plotted on either side of the cutoff, using the MSE bandwidth selector with triangular kernel weights.

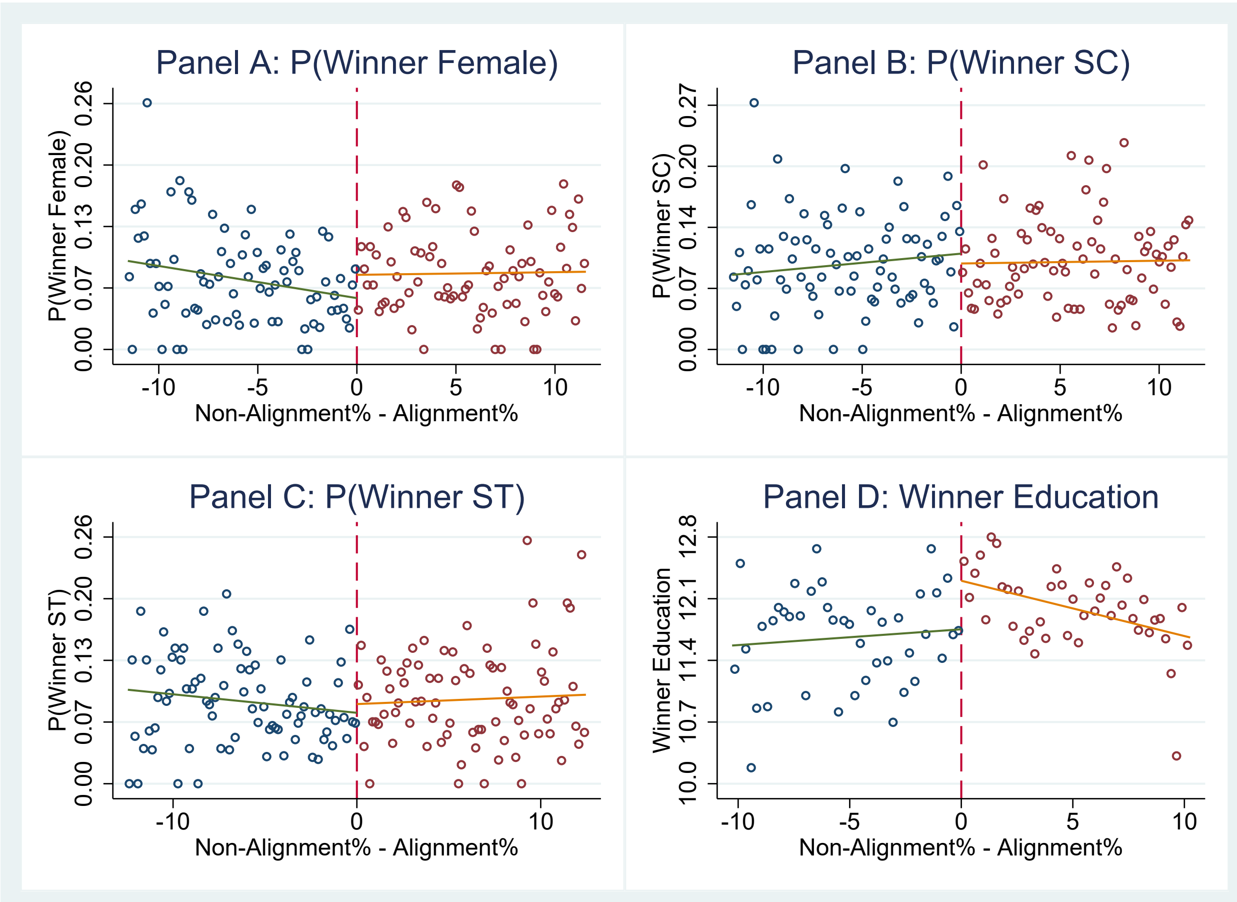


Figure 12: RD plots for candidate-level covariates

*Notes:* The covariates include winner gender, SC status, ST status, and education. The $x$-axis shows the vote-share difference between the top two candidates; positive values correspond to alignment, and negative values to non-alignment wins. Each dot represents the average outcome within a margin-of-victory bin, with bin sizes chosen by the mimicking-variance algorithm. Separate local linear fits are plotted on either side of the cutoff, using the MSE bandwidth selector with triangular kernel weights.

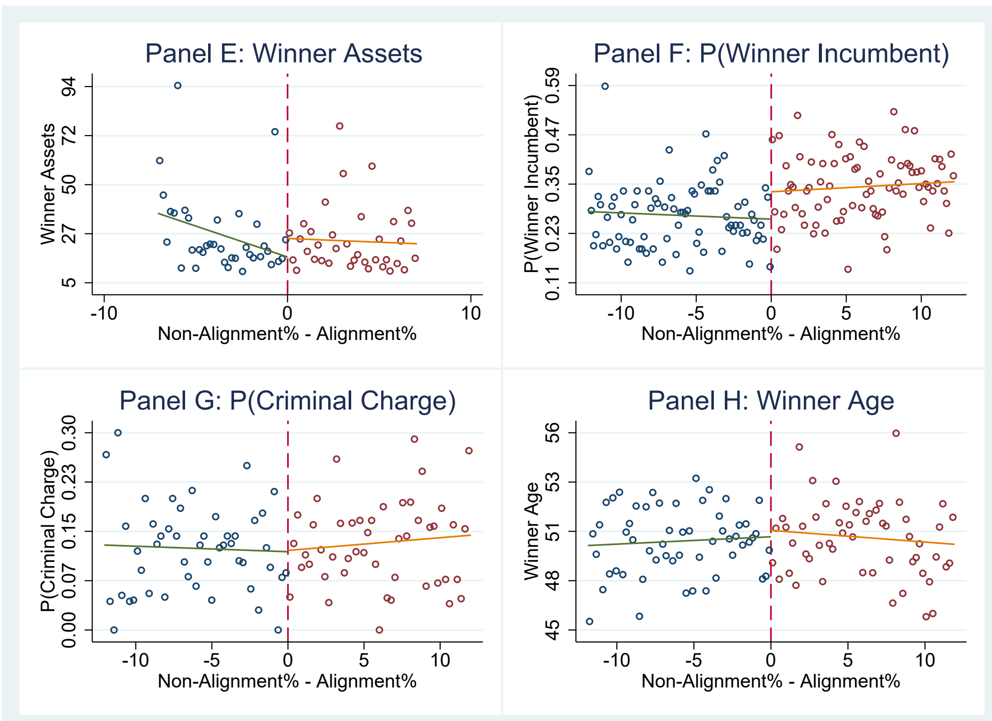


Figure 13: RD plots for candidate-level covariates

*Notes:* The covariates include winner assets, incumbency, criminal status, and age. The $x$-axis shows the vote-share difference between the top two candidates; positive values correspond to alignment, and negative values to non-alignment wins. Each dot represents the average outcome within a margin-of-victory bin, with bin sizes chosen by the mimicking-variance algorithm. Separate local linear fits are plotted on either side of the cutoff, using the MSE bandwidth selector with triangular kernel weights.

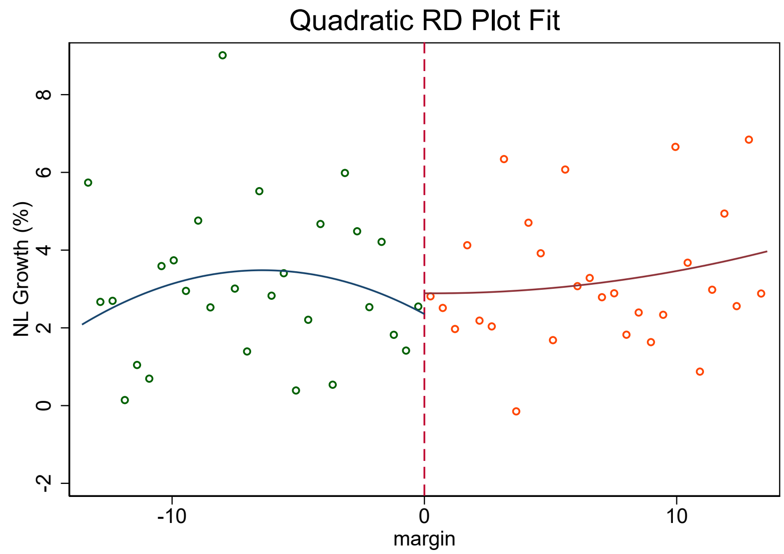


Figure 14: Quadratic fit of MP-MLA alignment on night-light growth
*Notes:* The $x$-axis is the victory margin between the top two candidates in percentage points. Positive values indicate alignment. The plot shows local **quadratic polynomial fits** on either side of the cutoff. The sample is restricted to constituency-years with minimum night-lights $\geq 2$, and the bandwidth is chosen by the MSE rule.

Table 7: Local quadratic RD estimates of MP–MLA alignment on night-light growth

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| RD_Estimate | 0.39 | 0.89 | 0.44 | 1.12 | 1.35 |
| | (1.37) | (2.01) | (1.08) | (1.52) | (1.88) |
| Bandwidth Algorithm | CER | CER/2 | MSE | MSE/2 | ±5pp |
| Bandwidth (pp) | 8.87 | 4.43 | 14.4 | 7.21 | 5 |
| Obs Left | 2230 | 1285 | 2986 | 1942 | 1439 |
| Obs Right | 3033 | 1572 | 4534 | 2510 | 1787 |
| Robust Standard Error | 1.87 | 2.66 | 1.43 | 2.09 | 2.50 |

*Notes:* Each column reports a separate local quadratic RD estimate of the effect of MP–MLA vertical alignment on night-lights growth with **no controls or fixed effects**. The running variable is the MLA margin of victory (percentage points), and the treatment is alignment with the constituency's MP. All specifications use a local quadratic polynomial on each side of the cutoff. Standard errors are clustered at the election level.

Table 8: RD Estimates of MP-MLA Alignment on Constituency-Level Covariates

**Panel A: Lagged Night-Lights and Constituency Size**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | NL Growth$_{t-1}$ | NL Growth$_{t-2}$ | NL Level$_{t-1}$ | Constituency Size |
| RD_Estimate | 2.95 | -0.81 | 0.43 | -606.5 |
| | (2.04) | (2.44) | (0.70) | (2338.9) |
| Bandwidth (%) | 13.3 | 15.4 | 11.7 | 11.4 |
| Obs Left | 1224 | 1224 | 1704 | 2512 |
| Obs Right | 1500 | 1545 | 2127 | 3179 |
| Robust SE | 2.39 | 2.85 | 0.82 | 2747.6 |

**Panel B: Turnout and Reservation Status**

| | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| | Turnout | P(SC Reserved) | P(ST Reserved) | P(Not Reserved) |
| RD_Estimate | -0.57 | 0.0040 | -0.00032 | -0.0024 |
| | (0.69) | (0.018) | (0.016) | (0.021) |
| Bandwidth (%) | 11.6 | 13.4 | 13.6 | 15.7 |
| Obs Left | 2537 | 2767 | 2786 | 2982 |
| Obs Right | 3202 | 3595 | 3616 | 3977 |
| Robust SE | 0.82 | 0.021 | 0.019 | 0.024 |

*Notes:* RD_Estimate reports the coefficient $\beta_1$ from Equation 1, which implements a local regression discontinuity design with the MLA margin of victory as the running variable and allows slopes to differ on either side of the cutoff. Bandwidths are chosen using the MSE-optimal selector. "Obs Left" and "Obs Right" report the number of observations just below and just above the cutoff, corresponding to non-aligned and aligned winners, respectively. The polynomial order is 1. Robust standard errors, clustered at the election level, are reported in parentheses.

Table 9: RD Estimates of MP-MLA Alignment on Candidate-Level Covariates

**Panel A: Candidate Demographics**

| | (1) P(Winner Female) | (2) P(Winner SC) | (3) P(Winner ST) | (4) Winner Educ |
|---|---|---|---|---|
| RD_Estimate | 0.030** | -0.017 | 0.014 | 0.52*** |
| | (0.014) | (0.016) | (0.015) | (0.18) |
| Bandwidth (%) | 11.6 | 11.6 | 12.5 | 10.3 |
| Obs Left | 2511 | 2537 | 2658 | 1181 |
| Obs Right | 3175 | 3200 | 3383 | 1399 |
| Robust SE | 0.015 | 0.019 | 0.017 | 0.21 |

**Panel B: Candidate Characteristics**

| | (5) Winner Assets | (6) P(Winner Incumbent) | (7) P(Winner Criminal) | (8) Winner Age |
|---|---|---|---|---|
| RD_Estimate | 1.23 | 0.072*** | 0.0055 | 0.071 |
| | (7.23) | (0.024) | (0.024) | (0.70) |
| Bandwidth (%) | 7.08 | 12.2 | 12.1 | 11.9 |
| Obs Left | 929 | 2624 | 1335 | 1613 |
| Obs Right | 1082 | 3330 | 1606 | 1988 |
| Robust SE | 8.59 | 0.028 | 0.028 | 0.83 |

*Notes:* RD_Estimate reports the coefficient $\beta_1$ from Equation 1, corresponding to the interaction between alignment and the MLA margin of victory in a local regression discontinuity design. The running variable is the MLA margin of victory (percentage points), and the specification allows slopes to differ on either side of the cutoff. Bandwidths are selected using the MSE-optimal algorithm. "Obs Left" and "Obs Right" report the number of observations just below and just above the cutoff, corresponding to non-aligned and aligned winners, respectively. The polynomial order is 1. Robust standard errors, clustered at the election level, are reported in parentheses.

Table 10: Effect of MP-MLA Alignment on Night-Light Growth by State Characteristics

| | *Dependent variable: Growth of Night Lights* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Panel A: BIMAROU States** | | | | |
| RD Estimate | -2.94 | -2.36 | -0.71 | -1.17 |
| | (5.35) | (4.91) | (5.67) | (5.58) |
| Bandwidth Size | 6.56 | 9.04 | 4.52 | 5.00 |
| No. of observations | 350 | 458 | 271 | 295 |
| Bandwidth Type | CER | MSE | MSE/2 | ±5pp |
| Robust SE | 5.78 | 5.68 | 6.65 | 6.57 |
| **Panel B: Least Developed States** | | | | |
| RD Estimate | 3.56** | 2.89** | 4.56** | 4.39** |
| | (1.61) | (1.36) | (1.98) | (1.87) |
| Bandwidth Size | 6.50 | 9.20 | 4.60 | 5.00 |
| No. of observations | 1321 | 1799 | 942 | 1038 |
| Bandwidth Type | CER | MSE | MSE/2 | ±5pp |
| Robust SE | 1.73 | 1.57 | 3.03 | 2.86 |
| **Panel C: High Corruption States** | | | | |
| RD Estimate | -3.74 | -3.29 | -2.60 | -1.90 |
| | (2.79) | (2.30) | (3.36) | (3.57) |
| Bandwidth Size | 8.23 | 11.49 | 5.75 | 5.00 |
| No. of observations | 790 | 1041 | 587 | 529 |
| Bandwidth Type | CER | MSE | MSE/2 | ±5pp |
| Robust SE | 3.03 | 2.78 | 4.66 | 4.94 |
| **Panel D: Rich States** | | | | |
| RD Estimate | -1.27 | -1.04 | -1.89 | -1.56 |
| | (1.34) | (1.12) | (1.57) | (1.94) |
| Bandwidth Size | 10.08 | 14.57 | 7.29 | 5.00 |
| No. of observations | 1958 | 2594 | 1527 | 1078 |
| Bandwidth Type | CER | MSE | MSE/2 | ±5pp |
| Robust SE | 1.46 | 1.34 | 2.45 | 3.20 |

*Notes:* Standard errors clustered at the constituency level in parentheses. Each column represents a separate RD regression of night-light growth on co-partisanship, using a triangular kernel and local linear specification. Bandwidths are chosen using alternative rules (CER, MSE, MSE/2, and fixed ±5pp). Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 11: Impact of MP–MLA Alignment on Night-Lights Growth in Least-Developed States with Controls

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| RD_Estimate | 3.56** | 2.38 | 3.16 | -0.12 | 2.89** | 1.75 | 1.84 | -0.20 |
| | (1.62) | (1.53) | (2.48) | (1.74) | (1.36) | (1.29) | (2.11) | (1.45) |
| Bandwidth Algorithm | CER | CER | CER | CER | MSE | MSE | MSE | MSE |
| Bandwidth (%) | 6.50 | 6.50 | 6.50 | 6.50 | 9.20 | 9.20 | 9.20 | 9.20 |
| Obs Left | 534 | 528 | 269 | 269 | 697 | 690 | 346 | 346 |
| Obs Right | 787 | 782 | 412 | 412 | 1102 | 1096 | 604 | 604 |
| Robust Standard Error | 2.49 | 2.39 | 4.16 | 2.79 | 2.05 | 1.95 | 3.30 | 2.27 |
| Candidate Controls | N | Y | Y | Y | N | Y | Y | Y |
| Constituency Controls | N | N | Y | Y | N | N | Y | Y |
| FE | N | N | N | Y | N | N | N | Y |

*Notes:* All specifications include controls as well as year and state fixed effects. Standard errors are clustered at the election level. Bandwidths are chosen using alternative selection rules (CER, MSE, MSE/2, and a fixed ±5 percentage-point window).

Table 12: Effect of Vertical Alignment by Candidate and Party Characteristics

| **Dependent Variable** | **Growth in Night Lights** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Panel A. Ruling vs Non-Ruling** | | | | | | | |
| | **Non-Government (Non-Ruling)** | | | | **Government (Ruling)** | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Vertical Alignment | -2.070 | -1.425 | -1.065 | -1.402 | 1.918 | 1.354 | 1.673 | 1.694 |
| | (2.108) | (1.760) | (2.985) | (2.501) | (2.097) | (1.748) | (3.024) | (2.437) |
| Bandwidth size | 7.644 | 11.13 | 3.822 | 5.564 | 9.482 | 14.16 | 4.741 | 7.082 |
| No. of observations | 2223 | 2840 | 1302 | 1721 | 3015 | 4208 | 1534 | 2272 |
| Bandwidth type | CER | MSE | CER/2 | MSE/2 | CER | MSE | CER/2 | MSE/2 |
| | **Panel B. Education (Below College vs College)** | | | | | | | |
| | **Below College** | | | | **College** | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Vertical Alignment | -1.024 | -0.414 | -2.420 | -1.504 | -0.664 | -0.750 | 0.112 | -0.154 |
| | (4.122) | (3.614) | (5.515) | (4.842) | (1.888) | (1.609) | (2.654) | (2.221) |
| Bandwidth size | 6.761 | 9.313 | 3.381 | 4.657 | 8.318 | 12.12 | 4.159 | 6.062 |
| No. of observations | 543 | 703 | 293 | 378 | 1867 | 2427 | 1024 | 1425 |
| Bandwidth type | CER | MSE | CER/2 | MSE/2 | CER | MSE | CER/2 | MSE/2 |
| | **Panel C. Incumbency (Non-Incumbent vs Incumbent)** | | | | | | | |
| | **Non-Incumbent** | | | | **Incumbent** | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Vertical Alignment | 1.038 | 0.405 | 2.017 | 1.035 | -1.975 | -1.260 | -1.948 | -2.414 |
| | (1.506) | (1.264) | (2.157) | (1.751) | (2.327) | (1.929) | (3.497) | (1.824) |
| Bandwidth size | 10.30 | 15.43 | 5.149 | 7.716 | 8.784 | 12.72 | 4.392 | 6.361 |
| No. of observations | 4170 | 5455 | 2315 | 3292 | 1565 | 2097 | 864 | 1219 |
| Bandwidth type | CER | MSE | CER/2 | MSE/2 | CER | MSE | CER/2 | MSE/2 |

Notes: Each column reports a separate RD estimate from a local linear specification with a triangular kernel. Standard errors (in parentheses) are clustered at the election level. Bandwidths are computed separately by subgroup using CER or MSE selectors; columns labeled "CER/2" and "MSE/2" use half the corresponding optimal bandwidth.

Table 13: Effect of MP–MLA Alignment on Night-Lights Growth by Years of Overlap

**Panel A: 1–2 Years of Overlap**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| RD_Estimate | 1.45 | 3.68 | 1.20 | 2.70 | 2.76 |
| | (1.87) | (2.59) | (1.59) | (2.14) | (2.16) |
| Bandwidth Algorithm | CER | CER/2 | MSE | MSE/2 | ±5pp |
| Bandwidth (pp) | 6.83 | 3.41 | 10.2 | 5.08 | 5 |
| Obs Left | 716 | 401 | 954 | 561 | 555 |
| Obs Right | 845 | 422 | 1190 | 646 | 633 |
| Robust Standard Error | 2.71 | 3.68 | 2.24 | 3.09 | 3.11 |

**Panel B: 3–4 Years of Overlap**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| RD_Estimate | -1.16 | -1.10 | -0.66 | -1.25 | -1.13 |
| | (1.14) | (1.62) | (0.96) | (1.32) | (1.39) |
| Bandwidth Algorithm | CER | CER/2 | MSE | MSE/2 | ±5pp |
| Bandwidth (pp) | 7.56 | 3.78 | 11.1 | 5.54 | 5 |
| Obs Left | 1239 | 686 | 1585 | 958 | 884 |
| Obs Right | 1687 | 852 | 2428 | 1275 | 1154 |
| Robust Standard Error | 1.69 | 2.54 | 1.40 | 2.03 | 2.15 |

*Notes:* Each panel reports local linear RD estimates of the effect of MP–MLA vertical alignment on night-lights growth. The running variable is the MLA margin of victory (percentage points). Bandwidths are chosen using alternative selectors (CER, MSE, their half versions, and a fixed ±5 percentage-point window, as indicated). Standard errors are clustered at the election level.

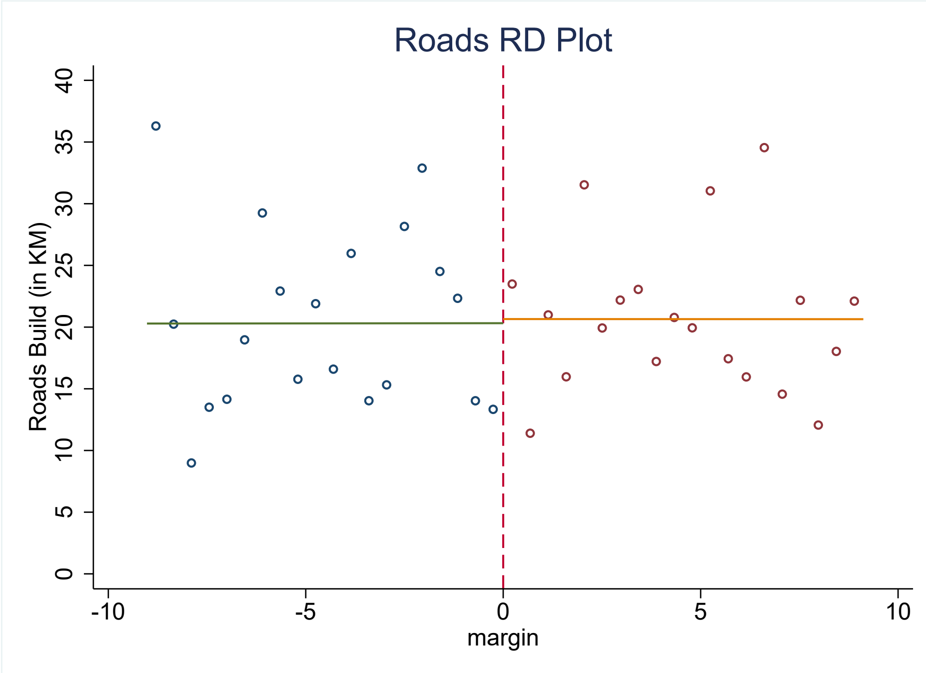


Figure 15: Impact of MP–MLA Alignment on Road Construction: RD Plots

*Notes:* The $x$-axis represents the MLA margin of victory (percentage points). Positive values correspond to aligned winners; negative values correspond to non-aligned winners. Dots represent binned local means, while lines show local linear fits estimated separately on each side of the cutoff. Bandwidth is selected using the MSE-optimal rule.

Table 14: Local Linear RD Estimates of MP–MLA Alignment on Road Construction

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| RD Estimate | 0.42 | 6.60 | -0.38 | 2.88 | 2.17 |
| | (4.35) | (5.74) | (3.86) | (5.04) | (4.88) |
| Bandwidth Algorithm | CER | CER/2 | MSE | MSE/2 | ±5pp |
| Bandwidth (pp) | 6.61 | 3.31 | 9.13 | 4.56 | 5.00 |
| Obs Left | 179 | 98 | 222 | 132 | 135 |
| Obs Right | 196 | 101 | 251 | 134 | 151 |
| Robust SE | 5.89 | 7.16 | 5.24 | 6.73 | 6.54 |

*Notes:* Each column reports a local linear RD estimate of the effect of MP–MLA co-partisanship on road construction (in kilometers). All regressions use a triangular kernel and robust bias-corrected standard errors clustered at the assembly constituency level, with no covariates or fixed effects.