AIIB WORKING PAPER No. 11 January 2023

TRANSPORT INFRASTRUCTURE AND LOCAL ECONOMY: EVIDENCE FROM THE GUJARAT RURAL ROADS PROJECT

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Abstract

This paper estimates the effects of a statewide rural roads project in Gujarat, India, on three aspects of the local economy: output, employment, and agricultural trade. Nighttime light intensity increased by 3.0-8.2 percent in treated villages relative to others in the post-project period, corresponding to a 0.8-2.4 percent increase in local output. The paper, using information from a rural public works program, finds evidence of higher employment associated with nonfarm work. Relying on the data of rural wholesale markets, it provides suggestive evidence on the positive impact of the project on cotton trade, a major cash crop in the region.

Acknowledgments

The authors are with the Economics Department at the Asian Infrastructure Investment Bank (AIIB). The paper is part of the Spatial Economic Analysis Initiative of the department. The paper does not represent the view of AIIB or that of its board of directors. Mert Kompil and Jiaqi Su provided valuable research input.

Keywords: rural roads, nighttime light, nonfarm employment, agricultural trade, India

JEL classification: O18, R42, R12, J43, O13

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The research greatly benefited from guidance and encouragement by Erik Berglof, Urjit Patel, and Rajat Misra from AIIB, and by Hans Timmer from the World Bank. The paper also benefited from the discussions at the AIIB Policy and Strategy Exchange-Economics Seminar and the World Bank South Asia Chief Economist Seminar. Special thanks for their constructive comments and suggestions go to Riccardo Crescenzi, Poelman Hugo, Dijkstra Lewis, Andres Pizarro, Abhijit Sen Gupta, Siddharth Sharma, Jangping Thia, and Wei Wenny Wang. We also thank Hari Bhaskar, Anzheng Wei, and Irene Bain for providing project background and information. All remaining errors are with the authors.

1. Introduction

The importance of infrastructure in facilitating growth and affecting welfare has long been studied, starting with Dupuit (1844), Aschauer (1989), and Barro (1990). More recently, there has been major progress in understanding the impact of transport investment. Baum-Snow (2007) and Duranton and Turner (2012) lead the empirical renewal. Donaldson (2018) and Heblich, Redding, and Sturm (2020) provide evidence on the general equilibrium effects. Overall, transport infrastructure stimulates migration, influences population distribution, increases agriculture and heavy products trade, and reorganizes economic activities (Duranton 2022; Redding and Turner 2015). However, as Aggarwal (2018) and Asher and Novosad (2020) point out, most existing studies have mainly looked at trunk transportation infrastructure projects. They have focused on their impact on cities or in the vicinity of cities. In the context of developing countries, urbanization remains an ongoing process. A major share of their population, especially the poorest, still resides in rural areas. A better empirical understanding of transport infrastructure in rural areas and local economy is important.

Aggarwal (2018) and Asher and Novosad (2020) fill this gap by being the first in the literature to estimate the development impact of rural transport projects causally. Both study a nationwide program in India, the Prime Minister's Rural Roads Program (PGMSY). To further shed light on the topic, this paper focuses on a statewide rural road project in the western Indian state of Gujarat, named Chief Minister Rural Road Program (Mukhya Mantri Gram Sadak Yojana or MMGSY; Gujarat Rural Roads hereafter). While the PMGSY connected large villages with more than 500 residents in Gujarat, the Gujarat Rural Roads project aimed at even smaller and more remote villages.

We explore the Gujarat Rural Roads project's natural experiment nature to estimate the causal impact of basic transport infrastructure in rural areas on the local economy. We construct a spatially granular data set that geocodes village-level information to corresponding administrative boundaries and integrates administrative, commercial road network, and open-source remote-sensing data. Finally, we use a difference-in-differences (DiD) design and estimate the project's effects on local output, employment, and agricultural trade in the short and medium term.

In theory, the development impact of rural transport projects is ambiguous. On the one hand, last-mile connectivity can integrate local economies with external markets, facilitating technological adoption in agriculture production, and stimulating mobility and nonfarm activities. On the other hand, these remote areas face other obstacles. Without sufficient complementary interventions, improved transportation connectivity may hollow out these places. In practice, the rural population makes up an influential political constituency. Rural road placement is not always random as a result. A concern is that transport projects are less effective in driving rural development than policymakers claim.

For example, Aggarwal (2018) and Asher and Novosad (2020) disagree on PGMSY's effectiveness, demonstrating the empirical nature of the question. Relying on a DiD design and district-level data, Aggarwal (2018) shows that the program led to lower prices and greater availability of nonlocal goods for consumption, suggesting greater product market integration. Rural households in the treatment areas also increased the use of agricultural technologies. In contrast, applying a fuzzy regression discontinuity design to village-level observations, Asher and Novosad (2020) find that the program had no major impact on agriculture outcomes, consumption, and income. However, it caused a significant reallocation of workers. The main economic benefit is the connection of rural workers to new employment opportunities outside.

In this paper, our motivation to focus on smaller villages stems from the heterogeneity in rural areas regarding access and opportunities. On the one hand, larger villages are more likely to be located near an urban area, making it accessible to more economic opportunities. In such a large village, any new infrastructure could complement existing conditions and increase the returns on investment. By contrast, smaller villages far from urban areas may not be able to reap the complementarities of a new infrastructure in the short and medium term. On the other hand, larger villages may start with more basic infrastructure and a higher baseline of economic activities. Therefore, if the marginal returns to new transportation infrastructure diminish, there could be a weaker impact in larger villages than in smaller ones.

This paper also adds to the empirical literature on rural transportation infrastructure by constructing spatially disaggregated panel data series for a major Indian state and conducting causal inference on its ambitious rural road project covering 33 districts. These panels include a village-level panel of nighttime intensity, a census-block-level panel of employment, and an agriculture-market-level panel of major crops. In contrast, Aggarwal (2018) relies on district-level panels, whereas Asher and Novosad (2020) depend on the data from two points in time at the village level. The granular panel data allow us to apply a DiD event study approach at these disaggregated levels. Similar to Asher and Novosad (2020), we can use the population threshold-based implementation rule to identify treated areas and to reduce endogeneity concerns.

Our results indicate positive development effects of the Gujarat Rural Roads project in the short and medium term. Following Henderson, Storeygard, and Weil (2012), we use nighttime light intensity as a proxy for local economic output. We show that light intensity increased by 8.2 percent in treated villages vis-à-vis others in the post-project period compared to the years before. This can correspond to a 2.1-2.4 percent additional local economic output. When restricting the control villages to those with a population between 500 and 1,000, the positive impact becomes smaller but remains statistically significant. The nighttime light intensity increased by 3.0 percent, corresponding to 0.8-0.9 percent higher local economic output.

We exploit the heterogeneity of the impact in terms of initial transport conditions. The project had lesser impact on treated villages with better initial road connectivity. This finding alludes to the hypothesis that there are diminishing returns to investment and the villages with initially better road infrastructure experienced smaller benefits.

Using information from the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), we find evidence of greater employment associated with nonfarm public work. We show that person-days worked in the program increased significantly in the treated census blocks vis-à-vis other blocks in the post-project period relative to the years before. Persons who demanded work also grew in tandem. Meanwhile, we only have suggestive evidence regarding the project's impact on agricultural trade. We show the quantity of cotton that arrived at local agriculture markets became larger, but the results are weak. We also find the arrival of groundnut did not respond to the project.

The rest of the paper is organized as follows. Section 2 introduces the Gujarat Rural Roads project and sketches out the economic rationale behind our analysis. Sections 3 and 4 describe the data sources and the empirical strategy. Section 5 presents the main results. Section 6 concludes.

2. Context and Analytical Framework

2.1. Project Background

The nationwide PGMSY was initiated in 2000 and funded and managed by the Ministry of Rural Development Department through state instrumentalities. Multilateral development banks, including the World Bank and the Asian Development Bank, have supported the project. The project cost USD40 billion by 2016 and USD56 billion by 2019. It currently continues in some states. In Gujarat, the PGMSY was to construct and improve rural roads to all villages with more than 500 people in the plains and more than 250 people in hilly, tribal, and desert areas. By 2014, the state had achieved 99.6 percent of its PMGSY targets in road projects, with only a few targeted large villages still to be connected.[1]

To extend the benefits of rural road connectivity to the areas left out by the PMGSY, the government of Gujarat launched the MMGSY (Gujarat Rural Roads project hereafter) in 2016/2017. It was designed to connect the road network to villages with a population below 500 people in the plains and below 250 people in the hilly, tribal, and desert areas. The Roads and Buildings Department of the state government oversaw the planning and implementation of the overall project. Phase 1 of the project lasted between 2016/2017 and 2018/2019. It was designed to provide all-weather rural roads to villages in 33 districts of the state by constructing and upgrading district and farm-to-market roads for villages where year-round connectivity was not available. AIIB loaned USD329 million to finance 81.6 percent of the project cost of phase 1. In total,

[1] See PMGSY's website: http://omms.nic.in/

13,581.67 kilometers of rural road construction/improvements were completed in the phase.[2]

2.2. Economic Rationale

Rural roads help residents move between a village and external areas, potentially increasing their access to markets. Greater access to external markets could positively affect local economic output through multiple channels. Regarding the agricultural product market, it will be cheaper to transport crops to formally distant markets, resulting in less use of middlemen and higher income for farmers, especially from cash crops. In the short to medium term, prices of productive inputs such as fertilizers and pesticides will converge toward external markets, stimulating their use and agricultural production. Farmers may adopt better technology because of information externalities associated with greater market access. Increased access to the credit market may also facilitate input use and technology adoption.

The impact on nonfarm production would work through similar channels, including access to the product market, inputs, information, and credit. At the same time, wages will adjust accordingly, triggering labor reallocation between farm and nonfarm jobs toward a more efficient distribution in the village. Finally, increased access to labor markets can improve short- and long-term labor mobility and further enhance the allocation efficiency of rural labor.

In this paper, we first aim to capture the aggregated impact on local economic output. We do so by using nighttime light intensity at the village level as a proxy of production. The literature has increasingly applied nighttime light to measure economic growth when traditional socioeconomic data are of poor quality or missing. A positive and significant elasticity has been established between changes in luminosity and economic growth (Henderson, Storeygard, & Weil, 2012). In India, nighttime light is used to analyze the impact of demonetization, regional convergence, and the COVID-19 pandemic (Beyer, Franco-Bedoya, and Galdo, 2020; Chanda and Kabiraj, 2020; Chodorow-Reich et al., 2020). Admittedly, nighttime light data are very noisy over time. Our spatial unit of analysis is also much smaller than existing studies on India, which have assessed state- or district-level variations. However, we take on a DiD approach that is particularly suitable for using luminosity data. Most of the noise is common across treated and untreated units and will not affect the robustness of the results. We hypothesize that better access would lead to more economic activity, reflecting higher luminosity.

Next, we focus on the rural labor market. We explore how the project may influence nonfarm employment associated with a unique public work program, the MGNREGA. Initiated in 2005, it aims to enhance livelihood security for all adults willing to participate in unskilled manual labor in rural India. It is implemented as a demand-driven, rights-based wage employment program in which every rural household with such adults registers their interest to work. They are then guaranteed at least 100 days of

[2] See AIIB's website: https://www.aiib.org/en/projects/details/2017/approved/India-Gujarat-Rural-Roads-MMGSY.html

employment in public works per year. A quarter of rural households have participated in the program. While it is a small part of the labor market, the MGNREGA has been documented to attract the poor and the vulnerable.[3] But work rationing is reported as a major challenge: more participants like to work more days but cannot find work, and nonparticipants do not join because of the lack of work opportunities (Desai, Vashishtha and Joshi, 2015). We hypothesize that improved connectivity would encourage workers to sign up for the program and increase workers' access to jobs located far away. Increased access could help reduce work rationing.

Finally, following the literature (Donaldson 2018; Duranton, Morrow, and Turner, 2014), we turn to the trade of agricultural products in local markets. The most grown cash crops in Gujarat are cotton and groundnut. [4] We look at the quantity of these two crops that arrived at the rural wholesale markets. Farmers in India can directly sell their crops in these large markets (*mandis*, formally called agricultural produce marketing committees or APMCs), which cover villages with the same pin code. Typically, auctions occur in these markets, and the winning bidders purchase the crops from the farmers. Alternatively, farmers would sell their produce to a middleman (Arthiyas), especially in the absence of good road networks. The middleman buys the commodities from different farmers and then visits larger APMCs to sell the crops to the wholesaler. We expect that, in both cases, the improvement in road connectivity would increase the quantity of arrivals in these markets because the transport costs to the markets would fall immediately.

3. Data

The official census population data and the administrative boundaries of the villages and towns are extracted from the South Asia Spatial Database, compiled by the World Bank (Li et al., 2016).[5] The boundaries are created by digitizing and georeferencing the Administrative Atlas of India. Using geocodes provided by the Census of India 2011 and a fuzzy matching methodology, the database matched population data with the boundaries, allowing us to identify treated villages and link treatment with nighttime light data.

Road information for India is from a commercial data provider, HERE Technologies. It includes road links, types, speed assumptions, and other auxiliary information sufficient to build a nationwide road network and compute travel time. We use the data to create the road network for 2015 and 2020, respectively. Please see Kompil et al. (2022) for details on road network building.

[3] The program is also found to be the first opportunity for many females to earn cash income and has significantly empowered women.
[4] Wheat is also a major crop in Gujarat. We do not consider it in our analysis because it is a stable crop with government procurement targets.
[5] See the data description: https://collaboration.worldbank.org/content/sites/collaboration-for-development/en/groups/research-partnership-for-sustainable-urban-development/groups/spatial-development-research/documents.entry.html/2016/05/24/a_spatial_databasef-qJjy.html

Nighttime light data are extracted from the Annual VIIRS-DNB (Version 2) global nightlight data provided by the Earth Observation Group (EOG) at the Colorado School of Mines. The EOG research team has cleaned these data by removing light noises. The data cover nighttime light from 2012 to date, with consistent data processing methods allowing users to compare changes over time (Elvidge et al., 2021). We first extract the data for Gujarat at the 15-arc second resolution level and the annual frequency for 2014 and 2020.[6] Then, to transfer into village-level data, we intersect the raster of light data with the village-level administrative boundaries and aggregate the pixel-level light radiation within each village. This gives us the total nighttime light intensity at the village level. Appendix 2 illustrates the computed intensity.

The MGNREGA data are publicly available on the MGNREGA Public Data Portal maintained by the Ministry of Rural Development.[7] Annual data on persons who demanded work and person-days worked under the program are obtained. The data are at the census block level. Each block comprises multiple villages, but is less aggregated than a district. Data for all census blocks in Gujarat from 2014 to 2019 are used.

Market-level quantity arrivals of agriculture products are extracted from the Agricultural Market Portal Agmarket.nic.in.[8] These data are available daily for a wide range of crops sold at the APMCs (*mandis*). Typically, auctions occur in these markets, and the winning bidders purchase the products from the farmers.[9] To minimize the volatility in the arrivals, we aggregate the data to a monthly frequency to take care of daily fluctuations for the baseline analysis, and then to a yearly basis for robustness checks. These data are collected at the pin code level. A pin code area is formed by several villages but is smaller than a district. Data for cotton and groundnut and for all pine code areas in the state from 2014 to 2019 are extracted.

4. Empirical Strategy

4.1. Identification of Treatment Area

A causal analysis of the economic impact of roads requires a credible identification strategy. Existing literature has applied different approaches to address the challenge, including instrumental variables and quasi-experiments (Duranton & Turner, 2012). An analogy to the PMGSY, the Gujarat Rural Roads project follows a pre-specified rule for implementation and presents a suitable setting for causal inference. As described earlier, the project targets villages below a population threshold to complement the PMGSY. This rule-based implementation presents a quasi-experimental variation of

[6] See the data source: https://eogdata.mines.edu/nighttime_light/annual/v20/. We used the file, VNL_v2_npp_YEAR_global_vcmslcfg_cTIME.average.tif.gz.
[7] See the MGNREGA Public Data Portal: https://mnregaweb4.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx
[8] See the Agricultural Market Portal: http://agmarknet.nic.in/agmarknetweb/
[9] In smaller APMCs, the bidding process usually involves calling out the prices like how it is traditionally done in an auction. Some larger APMCs with access to technology may employ digitized bidding.

road provision. The project targets the areas not covered by the PMGSY and permits us to have a clean identification of treated areas. By succeeding the PMGSY, the project has limited overlap with the former in terms of project time and allows the impact of the PMGSY to play out largely.

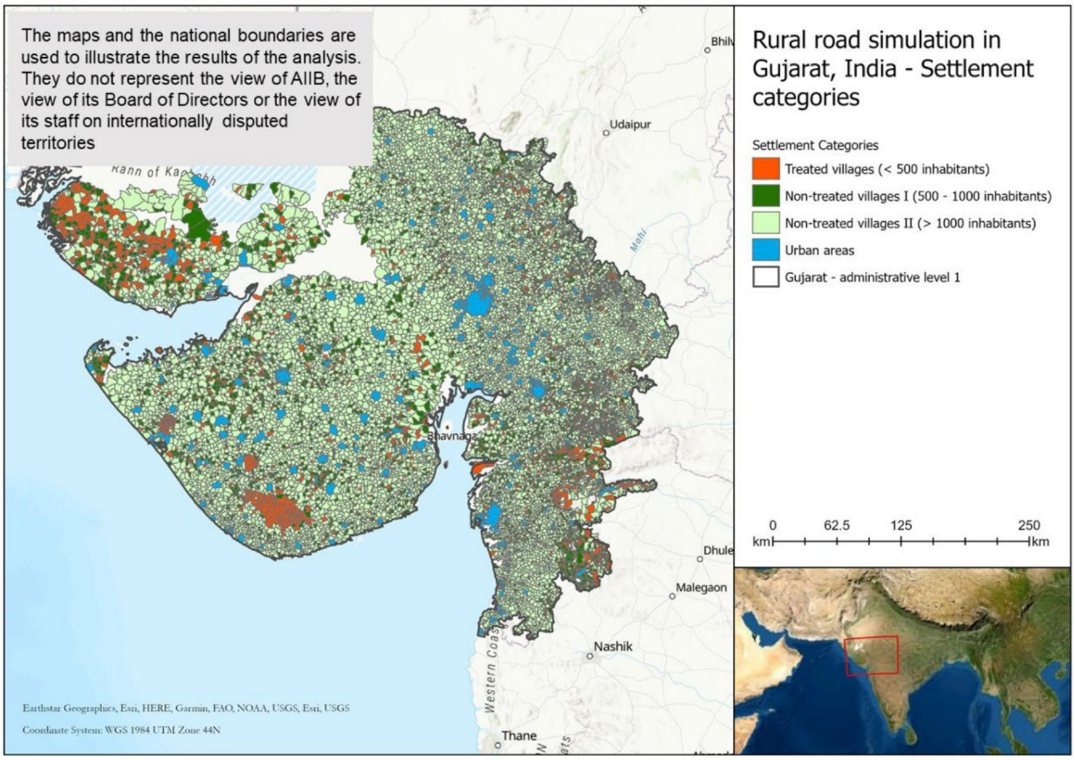
We rely on the project implementation rule and identify villages in Gujarat with a population below the 500 people threshold as the treated areas. It is in the spirit of a sharp regression discontinuity design with population as the running variable. We first consider all other villages in Gujarat not targeted by the project as controls. Then, as robustness checks, we define a more restrictive control group by including villages with a population between 500 and 1,000. Our control areas differ from those used by the previous studies because all-weather roads have connected these control villages through previous projects, including the PMGSY.

The final village-level sample included 22,114 Gujarat villages reported with population information by the 2011 Census of India and was matched with the digitized village-level administrative boundaries. Classified as treated areas are 2,867 villages with a population below 500. Control areas are 3,889 villages with 500 to 1,000 people, and the rest above 1,000. Figure 1 presents the geographic distribution of these treated and control villages. The first panel of Table 1 reports the average nighttime light intensity of the sample villages before the project (2014-2016). The treated villages are associated with lower light intensity than the control villages. Among the control villages, smaller ones are associated with lower light intensity.

MGNREGA employment data are available only for census blocks and agriculture product arrivals information at the pin code level. To identify treated and control areas for these outcome variables, we compute a synthetic measure of treatment using treatment intensity. Taking census blocks as an example, we compute the share of villages with a population below 500 in a census block in Gujarat. We then identify the census blocks with shares above the 75th percentile of the distribution as treated areas. Out of the 217 census blocks, 57 are treated areas. For control areas, we first consider the census blocks with shares below the 25th percentile and then conduct robustness analysis using all blocks with shares below the 75th percentile as controls. The second panel of Table 1 presents the average employment of the census blocks before the project. The treated areas are characterized by more people demanding work and more actual employment through MGNREGA.

The classification of agriculture markets follows the same methodology. The third panel of Table 1 presents the average monthly arrivals for cotton and groundnut across the treatment and control areas during the pre-project period. The treated areas registered lower arrivals on average for both crops.

Figure 1. The Geographic Distribution of the Treated and Control Villages



Note: Urban areas include officially designated urban areas and areas without population information.

Before formally estimating the impact on the local economy, we want to establish the first-order effect of the Gujarat Rural Roads project on connectivity. While we do not have detailed project road data, we have obtained information on the 2020 road network in India. We simulate the impact by downgrading the speed categories of roads crossing the treatment villages. For roads of different speed categories, we downgrade them by one-speed category, which mimics the road project design. We define the accessibility of a place as the population that can be reached within a 90-minute drive using the existing network, and transport performance as the ratio of accessibility to the population reached within a 120 km radius (Dijkstra Poelman, and Ackermans, 2019; Kompil et al., 2022).

We find that, on average, accessibility increases by 800,000 people; that is, residents of the treated villages can reach 800,000 more people in a 90-minute drive. In addition, transport performance for these villages increases substantially by four percentage points, reaching 20 percent or the average performance across all rural areas in India, including large villages (Appendix 2).

Table 1. Summary Statistics
(Average 2014-2016)

Village Group	**No. of Villages**	**Nighttime Light Intensity** (nW/cm2/sr)	**Nighttime Intensity** (ln)
Treatment (population < 500)	2,867	7.6	1.6
Control (population 500-1000)	3,889	13.6	2.0
Control (population >1000)	15,358	29.3	2.7

Census Block Group	**No. of Census Blocks**	**Person-days**	**Person-days** (ln)	**Persons Who Demanded Work**	**Persons Who Demanded Work** (ln)
Treatment (>75%)	57	116,314	10.9	6,998	8.1
Control (<75%)	160	81,951	10.8	4,627	8.0
Control (<25%)	53	67,045	10.6	4112	7.8

Agricultural Market Group	**No. of Markets**	**Arrivals** (Tons)	**Arrivals** (ln)
Cotton			
Treatment (>75%)	41	50	2.9
Control (<75%)	65	117	3.6
Control (<25%)	15	71	3.2
Groundnut			
Treatment (>75%)	27	24	2.5
Control (<75%)	57	49	2.6
Control (<25%)	19	40	2.5

Note: The numbers are annual averages for nighttime light intensity and MGNREGA employment, and monthly averages for agricultural market arrivals.

4.2. Econometric Specifications

We estimate the impact of the Gujarat Rural Roads project using a DiD design. Both standard two-way fixed-effects DiD specification and DiD event study specification are applied.

The standard DiD specification can assess the average treatment effect. The estimation equation for an outcome variable of interest, y, can be written as the following:

$$y_{it} = \sum_{t=t_0}^{t=T} \beta * MMGSY_i * Post2016_t + \gamma * MMGSY_i * Trend_t + \alpha_i + \delta_t + \epsilon_{it} \qquad (1)$$

Where subscription i denotes villages, census blocks, or agriculture markets (depending on the outcome of interest), and t denotes time (between the initial and the last period). α_i denotes the cross-section fixed effects that control for any time-invariant location characteristics, such as the climatic conditions, soil structure, and other persistent socioeconomic characteristics of the village that may directly affect its economic activity. δ_t denotes the time-fixed effect that controls for macroeconomic shocks affecting all villages uniformly, such as the demonetization shock and the COVID-19 pandemic.

$MMGSY_i$ is an indicator variable for whether location i has been identified as being treated or not. $Post2016_t$ indicates whether it is after the Gujarat Rural Roads project was completed. In this case, β estimates the difference in the average performance between the treatment and control areas after 2016 relative to the years before. It captures the average treatment effect of having access to the project road in the short and medium term. A legitimate concern is that areas with a larger population have a different growth trend, which may bias the estimate on β. An interaction term between $MMGSY_i$ and a time trend is introduced to address this issue.

We apply the DiD event study to formally test the parallel trends assumption required for the validity of the DiD strategy and to shed more light on the project effect over time. The specification for an outcome variable of interest, y, takes the following form:

$$y_{it} = \sum_{t=t_0}^{t=T} \beta_{year} * MMGSY_i * Year + \alpha_i + \delta_t + \epsilon_{it} \quad (2)$$

Where t denotes time. $Year$ takes the value of 1 for the respective year. The reference year is 2016 because it is the year before the project was implemented. . Everything else has the same meaning as in equation 1. β_{year} denotes the DiD coefficient corresponding to the respective year, with β_{2016} equaling zero by design. Thus, β_{year} estimates the differences in the average performance between the treatment and control areas in another year relative to 2016. For the validity of the research strategy, if the event study coefficients in the pre-project period are statistically insignificant, it indicates that the treatment and control areas are similar and the treatment is exogenous to the group.

5. Results

5.1 Local Output

Column 1 of Table 2 presents the baseline results from equation 1 when the nighttime light intensity is the outcome of interest. In contrast, panel a of Figure 2 plots the baseline DiD coefficients of the event study. On average, the nighttime light intensity increased by 8.2 percent after implementing the Gujarat Rural Roads project in the treated villages relative to the control ones. More specifically, the DiD coefficient increased to about 9 percent in 2017 and 2018 before declining in 2019. All these coefficients are relative to the control group and the year 2016. Thus, the decline in 2019 does not indicate an absolute decrease in nighttime light intensity in the treated villages.

Regarding the validity of the estimation strategy, we find that the DiD coefficients of the event study in the pre-project period are not statistically significant. It implies that the treatment and control groups show parallel trends. Endogenous treatment choice would be a concern if the coefficients were significant during the pre-project period. Thus, this result gives us confidence in the DiD estimates.

In column 2 of Table 2 and panel b of Figure 2, we report the results from restricting the control group to the villages with a population of 500 to 1,000. The parallel trends assumption still holds as the pre-project event study coefficients remain insignificant. The magnitude of the average coefficient becomes smaller (0.03), but it remains statistically significant. Therefore, our key results are robust when the treated villages are compared to those with similar sizes.

As a placebo test, we replicate the regressions but classify the villages with a population of 500 to 1,000 as pseudo-treated villages. We take the villages with 1,000 to 1,500 people as the control group and conduct the analysis. Column 3 of Table 2 presents the results. As expected, we find no significant change in the pseudo-treated villages relative to the controls in the post-project period.

To get the economic magnitude of the impact, we translate the changes in light intensity into changes in economic activity by relying on reported elasticity. Based on annual and long-term growth rate comparisons for a sample of 188 countries, Henderson, Storeygard, and Weil (2012) argue for an elasticity of GDP growth to light intensity growth of 0.3. Beyer et al. (2018) estimate this elasticity to be 0.25 for South Asian countries. Using these numbers as the upper and lower bounds of the elasticity, we estimate that the project results in 0.8-2.4 percent increase in local output in the treated villages relative to the control villages.

Next, we test whether the effects of new road construction on economic activity depend on the initial level of connectivity. On the one hand, a village with an existing network may accrue complementary benefits from new road construction. On the other hand, a village with low initial connectivity may have higher marginal benefits from new road construction. We test this question by interacting with the 2015 value of transport performance at the village level, TP_i, an indicator for connectivity, with the interaction term between $MMGSY_i$ and $Post2016_t$.[10] We find that the coefficient on the new term is negative and statistically significant. TP_i is positive and the greater value indicates better connectivity. Therefore, the results suggest that a new road has a smaller marginal effect on initially better-connected villages.

[10] See Appendix 2 for the methodology of computing *TP*.

Table 2. Effects on Nighttime Light Intensity

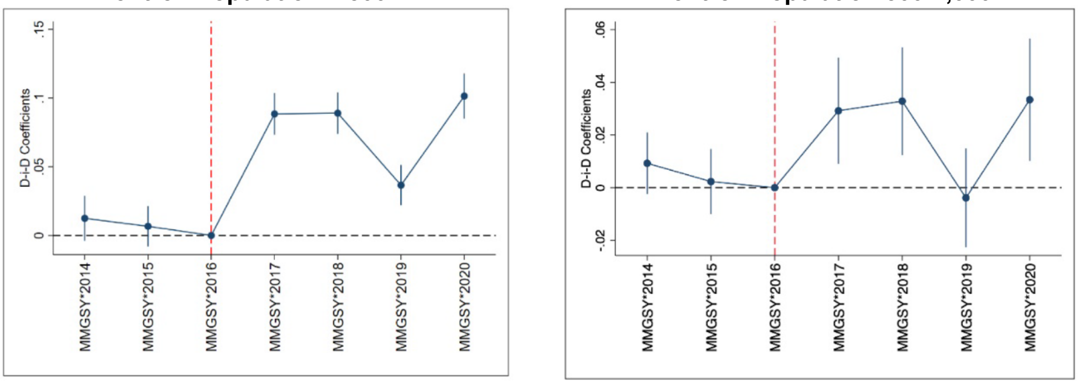
	Control: Population >500	Control: Population 500-1,000	Placebo Treated: Population 500-1,000 Control: Population 1,000-1,500
MMGSY* Post2016	0.082***	0.030***	0.008
	(0.008)	(0.009)	(0.007)
Constant	2.734***	2.081***	2.420***
	(0.001)	(0.002)	(0.002)
MMGSY* Time Trend	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	127743	47320	49406
Clusters	18223	6754	7053

Note: Standard errors clustered at the village level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2. Effects on Nighttime Light Intensity

a. **Control: Population > 500**

b. **Control: Population 500-1,000**



Note: The dots indicate the point estimates of the DiD coefficients of the event study, and the bar indicates the 95% confidence interval of the estimates.

Table 3. Initial Connectivity and Effects on Nighttime Light Intensity

	Control: Population >500	Control: Population 500-1,000
MMGSY*Post2016	0.107***	0.054***
	(0.013)	(0.013)
MMGSY*Post2016*TP	-0.001**	-0.001**
	(0.001)	(0.001)
Constant	2.734***	2.081***
	(0.001)	(0.002)
MMGSY*Time trend	Yes	Yes
Village FE	Yes	Yes
Year FE	Yes	Yes
N	127743	47320
Clusters	18223	6754

Note: Standard errors clustered at the village level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Local Employment

Table 4 presents the average project impact on persons who demanded work and person-days worked under the MGNREGA program. Figure 3 plots the event study coefficients. On average, persons who demanded work under the program increased significantly in the treated census blocks relative to the control areas. However, the impact is significant only when compared with the control blocks primarily consisting of larger villages. The same pattern is found for person-days worked.

Regarding the event study, the coefficients for 2014 and 2015 are not statistically significant, confirming the parallel trends assumptions. After the project started, there was a significant effect on work demanded and person-days worked in 2018. However, the coefficient for person-days worked declined in 2019, whereas that for work demanded increased slightly. This could indicate that the labor-market stress introduced by the COVID-19 crisis hit the smaller villages harder, which we did not control.

We want to mention one caveat. In many cases, rural roads are built by workers under the MGNREGA program. So, it is likely that some roads of the Gujarat project were built by the workers under the program as well. In such a case, higher employment may not be a good indicator for access to nonfarm job opportunities due to improved connectivity. It would just indicate the employment required for the construction of the rural roads project. However, if the labor demand for MMGSY construction drove the estimated effect, it should have shown up in 2017 when the program started without lags. Instead, the event study coefficient for 2017 is insignificant which suggests that the roads may not have been built by the workers under MGNREGA.

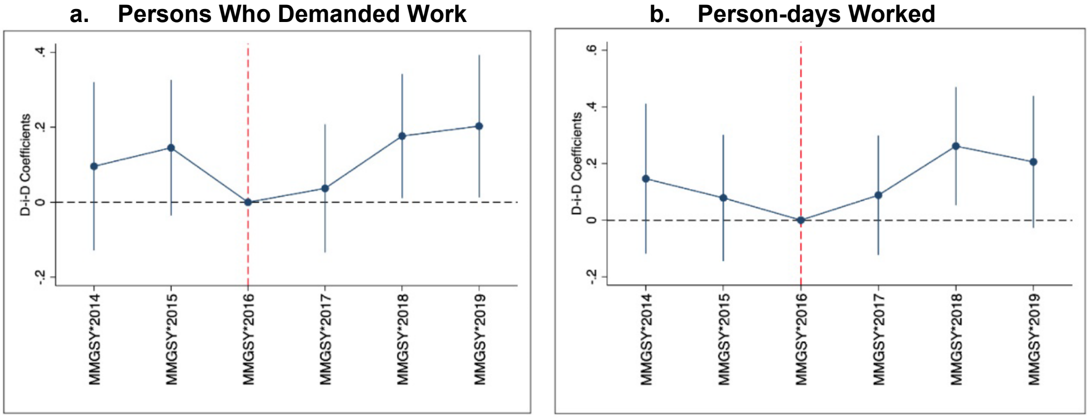
Table 4. Effects on MGNREGA Employment

	Persons Who Demanded Work		Person-days Worked	
	Treatment: >=75% Control: <25%	Treatment: >=75% Control: <75%	Treatment: >=75% Control: <25%	Treatment: >=75% Control: <75%
MMGSY* Post2016	0.194**	0.059	0.193**	0.110
	(0.089)	(0.069)	(0.090)	(0.082)
Constant	8.046***	8.160***	8.043***	11.086***
	(0.033)	(0.017)	(0.033)	(0.020)
MMGSY* Time trend	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	672	1326	672	1325

Note: Robust standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3. Effects on MGNREGA Employment

a. Persons Who Demanded Work **b. Person-days Worked**



Notes: The dots indicate the point estimates of the DiD coefficients of the event study, and the bar indicates the 95% confidence interval of the estimates. The control group includes the census blocks with a share of small villages (population < 500) below the 25th percentile.

5.3 Local Agricultural Trade

Table 5 reports the effects on the quantities of agricultural products that arrived in the wholesale markets (or APMCs). We use monthly data for the baseline analysis and yearly data as robustness checks. [11] We find suggestive evidence that improved road network facilitated the arrival of cotton in the treated markets. However, we find no evidence of increased arrivals for groundnut. On average, there were more arrivals of cotton in the markets within the treated pin code areas relative to those in the control areas. However, the results based on annual data do not show any effects. As discussed above, lower transportation costs likely stimulate farmers' supply of products. Agricultural productivity in the treated areas could also increase with improved access to pesticides, fertilizers, and learning. On the other hand, a better road network connects the smaller villages to larger markets, which may be located further away from the villages. In such a case, the crops may be diverted to the larger distant markets from the smaller nearer markets. Thus, the overall effect of improved road connectivity on agricultural trade may be ambiguous.

[11] The results of the robustness checks using yearly data and the event studies are available upon request.

Table 5. Effects on Arrivals at Agricultural Markets

	Cotton		Groundnut	
	Treatment: >=75% Control: <25%	**Treatment: >=75% Control: <75%**	**Treatment: >=75% Control: <25%**	**Treatment: >=75% Control: <75%**
MMGSY* Post2016	0.162	0.216**	0.308	-0.02
	(0.121)	(0.09)	(0.251)	(0.12)
Constant	2.599***	2.908***	1.972***	2.139***
	(0.060)	(0.02)	(0.117)	(0.03)
MMGSY* Time trend	Yes	Yes	Yes	Yes
Pin code FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1334	2640	1008	2274

Note: Robust standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusion

In this paper, we estimate the effects of the Gujarat Rural Roads project that connected small villages in 33 districts of the western Indian state with all-weather roads. The local economic impact of transport infrastructure in rural areas remains a much-debated empirical question. Projects targeting small and remote villages face more uncertainties in their effectiveness. Regarding the Gujarat Rural Roads project, our results support its positive impact on nighttime light intensity and public work-related employment. We also show suggestive evidence regarding increased arrivals in local wholesale markets for some cash crops.

Our analysis admittedly does not capture the same dimensions of welfare as Aggarwal (2018) and Asher and Novosad (2020). Instead, this study adds to the literature by focusing on a set of variables that can form longitudinal datasets for spatially granular units and capture three relevant aspects of the local economy in the short and medium term: output, nonfarm employment, and agricultural trade. Our results point to the heterogeneity of villages and, hence, the effects of rural transport projects. Moving forward, a better understanding of the heterogeneity through further partial equilibrium analysis and general equilibrium modeling is important. Future studies on the long-term economic effects of the same rural roads project would complement our results of the short- and medium-term outcomes. Another area worth exploring is the “network of networks” perspective through causally assessing the complementarity between transport and other investments in rural areas, such as digital infrastructure projects.

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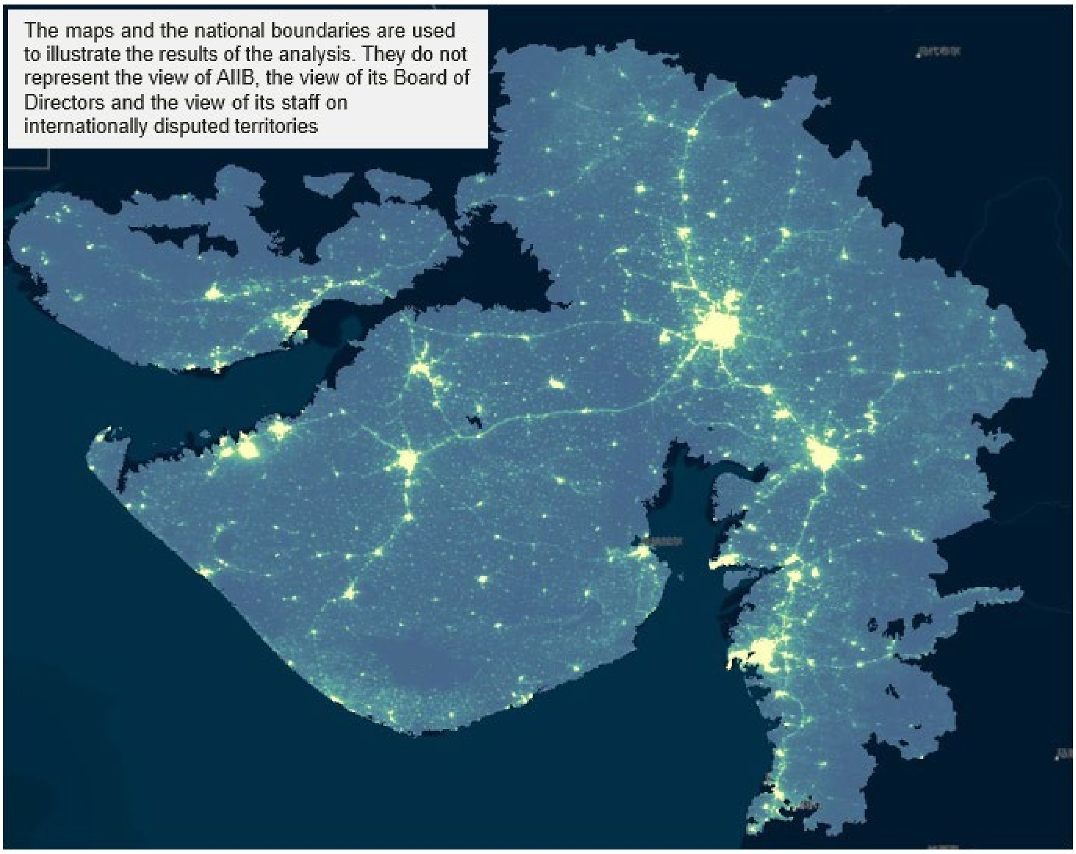
APPENDICES

Appendix 1. Nighttime Light Intensity

Figure A1. Nighttime Lights in Gujarat



Source: Authors' computation based on Earth Observation Group.

Appendix 2

We follow Dijkstra Poelman, and Ackermans (2019) to measure transport connectivity and compute three different indicators. Proximity is measured as the number of people reached within a 90-minute drive, assuming that one can drive at 80 km/hour in a straight line or, equivalently, the number of people reached within the 120 km radius. Accessibility is computed as the number of people reached within a 90-minute drive using the existing road network. Finally, transport performance is the ratio between accessibility and proximity. The computation is at the 1 km X 1 km pixel level and is then aggregated to the village level with population weights.

Figure A2 maps out the rural roads that are downgraded in the simulation, and Figure A3 presents the associated effects on transport performance. We select the roads for downgrading by intersecting the road network with the administrative boundaries of the treated villages. Among all roads crossing the treated villages, we reduce the speed category of the low-speed roads, including 344 km downgraded from 51 to 31 km/hour; 2,033 km roads from 31 to 11 km/hour; and 17,683 from 11 to 5 km/hour.

A comparison between the road network after the speed downgrading and the current one suggests a significant first-order impact of the Gujarat Rural Roads project on connectivity (Figure A3). Not surprisingly, the impact is concentrated in the treated villages. Accessibility increases by 800,000, i.e., residents of the treated villages can reach 800,000 more people in a 90-minute drive. Transport performance for these villages increases by four percentage points, reaching 20 percent or the average performance across all rural areas in India, including large villages.

Figure A2. Selected Rural Roads for Simulation

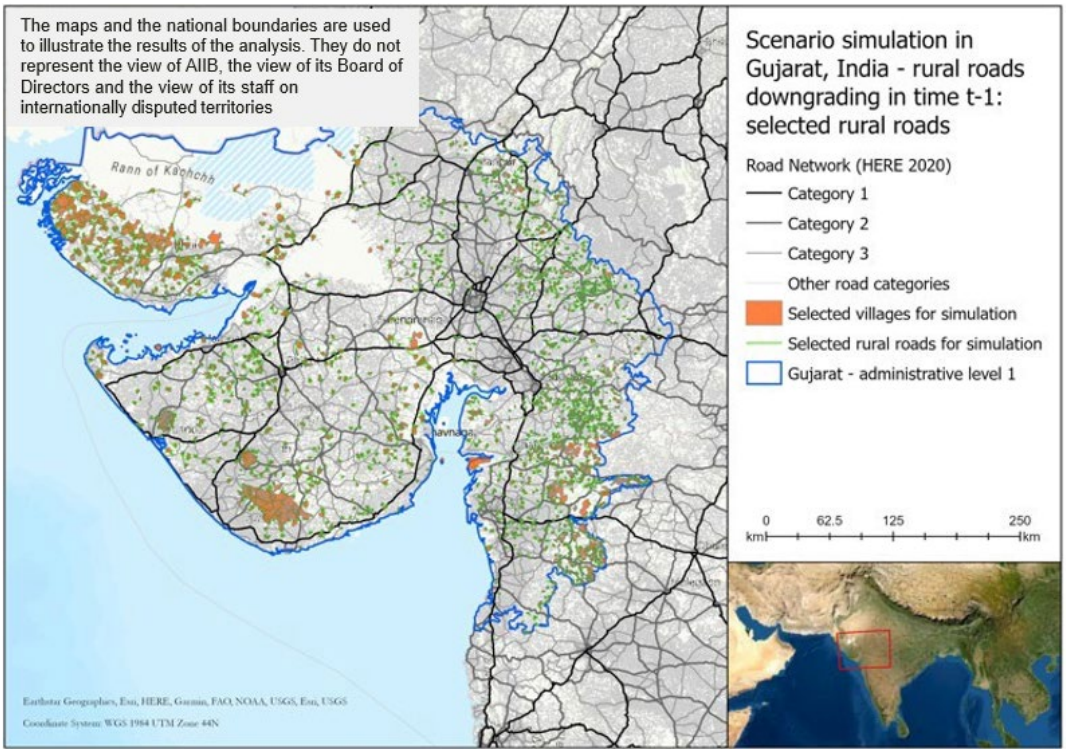


Figure A3. Simulated Effects on Transport Performance