Road Oft Taken: The Route to Spatial Development

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Abstract

Most estimates of the economic impacts of transit networks compare regions along routes to neighboring regions away from such routes. In the presence of spatial spillovers in economic activity such a method will underestimate the true effect of roads and railways. In this paper, I take into account spatial spillovers in estimating the overall impacts of transit networks in India. I use an empirical strategy relying on the historical placement of major cities: by connecting nodal cities with straight lines, I instrument for the endogenous placement of these networks. Using night-time luminosity data as a measure of economic activity, I estimate the parameters of a predictive model that incorporates these spillovers, which then performs well in an out-of-sample exercise. I find that being close to transit networks between cities led to greater economic activity in the 1990s and that such activity spread to neighboring regions, substantially increasing the overall impacts. Ignoring the spillovers produces income elasticities that are only 27% of the true overall effects of such routes. These geographic externalities led to a rapid rate of convergence in incomes across regions, highlighting how transit networks and spatial spillovers together, strongly determined the geographic spread and temporal changes in the economic development of the region.

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1 Introduction

Past work on transit networks that compares regions along the route to neighboring regions overlooks the fact that these neighboring regions are also affected by these routes because of spillovers across regions. If highways draw economic activity away from interior regions, and towards regions on the highway, then neighboring regions are essentially losing activity and the net effect of a highway may be closer to zero. If, on the other hand, activity along a highway spurs activity in neighboring regions, then the spillovers are positive, and comparing a highway region to a neighboring region will provide an underestimate of the overall impact of the highway. If these positive spillovers are large, then it may seem like there are no impacts of road and rail routes, when in fact the overall effects are in fact, even larger. To understand the full extent of the impacts of a route, I quantify the amount of spillovers, and describe the entire pattern of spatial development in a dynamic framework.

I study India, over two decades starting in 1992. This was a period of rapid growth, economic liberalization, and a period of upgrading the existing highways that connected major cities. Consistent with decreasing income differentials for regions along the route, I find that while substantial spatial inequalities existed at the beginning of the period, there was a rapid convergence across regions in the 1990s, as economic activity spreads from these routes to neighboring regions allowing them to catch-up. I find that ignoring these externalities would lead to estimates of infrastructure-income elasticities that are only 27% of the true overall impact of these routes. In 2012, a 1% decrease in distance from these routes raises incomes by only 0.06% ignoring spillovers, but overall incomes rise by 0.23% once spillovers are incorporated. These spillovers also drive the rapid rate of convergence in incomes across regions – I estimate a 4% rate of β-convergence which is twice as high as the rate in the cross-country literature (Barro and Sala-i Martin, 2004).

Better infrastructure is generally thought to aid development by reducing the costs of trade and migration, equalizing prices and facilitating the spread of ideas and technology. However, causal impacts of transit networks are hard to find for two reasons. First, the observed placement of these routes is endogenous. Richer regions have better roads, but this is not only because roads may lead to more development, but also because these regions have the capability to build better roads, and many roads were built in regions that were starting out on a path to prosperity. On the other hand, these routes may have been built to help struggling regions recover, and are more likely to be built in regions with suitable terrain and easier land acquisition policies. In order to obtain causal estimates, I use straight-line paths between nodal cities as instruments for the existence of transit networks. This allows me to study the overall impact of highways on regions between cities, in contrast to a world in which these cities were not connected by transit networks. In the first half of the paper, I discuss the empirical reduced form impacts of these routes on spatial development. I combine this with a multi-period differences-in-differences specification to find that being connected to transportation networks causes a region to be more developed than neighboring regions, but neighboring regions catch up over time.

Secondly, there is the issue of finding an effective 'control' group. In this paper, I find that neighboring regions will provide an underestimate of the true impacts due to positive spillovers. In order to tackle this issue, in the latter half of the paper (Section 6), I develop a simple model that captures these reduced form patterns, and then structurally characterize income growth and regional convergence in the presence of economic externalities. The model produces strong predictions for various parameters – namely, that the reduced form elasticity of income with respect to distance is a specific function of the extent of spillovers in economic activity, and the direct impact of distance from these routes. I test these predictions and show that the model does a good job of fitting the data in validation tests. With the help of the model and the empirical estimates, I determine the parameters of convergence and the extent of spatial spillovers across regions. I am able to use these causally estimated parameters to quantify the overall impact of these transit networks. Ignoring these spillovers would severely underestimate the true overall impacts of these routes.

Estimating such spillovers is essential for policy analysis, as positive externalities across regions suggest that the benefits of infrastructure projects are larger than previously thought. I also find that while the early construction of transit networks led to local development, there were diminishing returns in continuing to invest in and upgrade these highways. It would then be a better policy to connect other regions with newer road and rail routes, rather than upgrade already existing networks.

The road-map of this paper is as follows: Section 2 discusses the literature and the background motivating the identification strategy. One notable absence from the literature is a credible way to estimate and quantify the extent of spillovers across regions that magnify the overall impacts of these routes. In Section 3, I discuss the data I use, where I merge night-time lights data with data on road and rail routes, and other sub-district level indicators. Section 4 studies the reduced form effect of being along these straight-line paths that connect major cities, and Section 5 describes what happens to this relationship over time, including the effects of upgrading the highways. After which, I discuss a model in Section 6 that explains the patterns in the data described in Sections 4 and 5. The first part of the model focuses on standard neoclassical growth theory (Section 6.1) and the corresponding convergence in incomes across regions (Section 6.2). In Section 6.3, I introduce the role played by spillovers, and estimate the parameters of the model and rigorously test the predictions in Section 6.4. I use the estimated parameters of the model, including the extent of the spillovers, to determine the overall impact of theses routes in Section 6.5, and discuss the importance of these results in the context of the long literature on infrastructure projects in Section 7.

2 Transit Networks in India, China and the US

A number of papers follow the methodology first established by Chandra and Thompson (2000) and later built upon by Michaels (2008) to estimate the impacts of US inter-state highways.[1] These papers focus on non-metropolitan areas that lie on highways between the metros. In certain contexts, like India, such a strategy may not be enough. There are many possible routes between two metros, and the actual placement of the highway is endogenous – perhaps trying to connect growing rural areas, areas that are particularly poor, or areas with suitable terrain, land cover and easier land acquisition.

Two papers on China help tackle these endogeniety issues. Banerjee et al. (2012) use straight-lines to connect historical cities, and use this to predict the existence of transportation networks, which explain moderate differences in GDP per-capita, but no effect on income growth. Faber (2014) uses the construction of the Chinese National Highway system and combines it with a spatial instrument based on the 'least-cost' path of connectivity, that depends on terrain, water bodies and land cover.[2] Similarly, I connect historical cities in India, which were selected as nodal cities for a large highway-upgrading project, and study the impact on indicators that are closely related to economic activity, like the amount of night-time luminosity captured by satellites in this period.[3] However, rather than just comparing regions along these paths to neighboring regions (a 'control' group), I estimate the spillovers to the neighboring regions so as to pin down the overall causal impact of the transit network and the dynamic nature of convergence in incomes across regions.

Unlike other work, I focus on spatial spillovers and how they cause poorer regions to catch up. One crucial difference between the Chinese and Indian cases is the mobility of factors – while migration was highly regulated for many decades in the Chinese context,[4] there is unrestricted labor mobility in India, which would be especially useful in an analysis of spillovers across neighboring regions. In so far as access to transportation will have large impacts via migration, the Indian context would allow for studying these effects and be more relevant to contexts that do not have migration restrictions. Labor mobility in India is low (Munshi and Rosenzweig, 2016), and this may be due to the high costs of migration for regions that are not well connected to transportation networks.[5] The second big difference is the data used –

[1]See Redding and Turner (2015) for a discussion of models and identification methods in this literature.

[2]Two recent papers in the Chinese context study the urban spread and the shape of Chinese cities (Baum-Snow et al., 2014) and access to domestic and export markets (Baum-Snow et al., 2015). In fact, the study (Baum-Snow et al., 2014) also uses night-time lights data and shows that the presence of radial highways and ring-roads disperses populations from the center of the city to peripheral areas. My paper does not study cities, but rather the regions between cities.

[3]I refrain from using the 'least cost' path in the Indian context, since an instrument that relies on land cover, water bodies and terrain may introduce other sources of endogeniety. A region that is flat may grow faster than a hilly region for reasons unrelated to transit networks. A region that has less land cover may have been cleared for development purposes. Furthermore, regions with less land cover and flatter terrain are also more likely to be near cities. In my context, therefore, a simple 'straight-line' is arguably a cleaner instrument.

[4]From 1958-78 it was restricted, and then *hukuo* reforms were established to loosen but still regulate mobility.

[5]Even though labor mobility is low, capital is relatively more mobile in India (see e.g. Ghani et al. (2015)).

like the Chinese case, the Indian data on GDP at a sub-regional level is poor and problematic. Changes in data-collection methodology over time and across regions may well be correlated with regional development and access. Banerjee et al. (2012) also highlight other issues with the Chinese context: that a non-random sample of regions report GDP numbers, and which years those regions chose to report is also endogenous. It may therefore be better to use data collected from an external source – like the night-time lights data used by this paper. Last, I conduct a before-after analysis to look at the impact of a large upgrade under the National Highway Development Project (NHDP) to test whether additional investments into already existing networks matter, and find little benefits of these upgrades.

The highway system studied here connects the four nodal cities forming what is called the Golden Quadrilateral (GQ). Three of the four cities (Mumbai, Kolkata and Chennai) were chosen to be capitals of the British Presidencies as they were natural harbors and could be used as ports for trade. There was little economic activity in these three regions prior to the British, and not much of a pre-existing road network. The fourth (Delhi) was a major historical capital of various pre-Colonial empires, and was a British cantonment during the Raj.[6]

I focus on the period between 1992 and 2012. While the decades leading up to this period were burdened with sluggish growth, these two decades were a time of high and rapid development following the reforms of 1991 that came under a proclamation of 'Liberalization, Privatization, Globalization.'[7] Starting in 1999, the Golden Quadrilateral (GQ) project upgraded about 5,846km of already existing highways in India. The NHDP invested about US $71 billion in order to widen the national highways, and strengthen them for heavy traffic and truck transportation. While the proposal was approved in 1998, many projects started only in 2001. Most of the delays had to do with issues of land acquisition, which makes the placement of the final roads endogenous, and prompting the use of the 'straight-lines' between nodal cities.[8]

Ghani et al. (2015) focus on the upgrades in the late 1990s and look at the behavior of manufacturing firms. They find an increase in entry-rates for organized manufacturing firms within 10km of the highways, and modest impacts on other indicators.[9] They are careful to point

[6]Three cities were then chosen to be major British capitals for their natural harbors and strategic positioning of coastal forts – all reasons unrelated to being near land-based routes. A member of the British East India Company arrived near modern day Kolkata in 1690, and the British established Fort William in 1698, which gave rise to the modern Kolkata. A few decades before that, in 1639, the British had set up Fort St. George which grew into modern day Chennai. While on the other side of the peninsula, Francisco de Almeida, a Portuguese explorer, sailed into the deep natural harbor of the Mumbai islands in 1508, and the Portuguese acquired the islands in 1534. In 1661 the islands were given to the British as part of the dowry for Catherine of Braganza's wedding to Charles II. Delhi, on the other hand, only passed over to British hands in 1803.

[7]The reforms opened up major sectors of the economy to foreign trade and eventually some sectors to foreign investment, privatized many industries and cut down what is well known as the 'license-permit raj.'

[8]The junior Highways Minister told the Parliament that "Projects have been delayed mainly due to problems associated with land acquisition, shifting of utilities, obtaining environment and forest clearance, approval for road over bridges, poor performance of some contractors due to cash flow constraints and law and order problems in some states." The bulk of the projects were over by the end of 2006, but some alterations on additional phases of the project continue even as late as 2014.

[9]For other contemporaneous work related to the upgrades on market access within the context of a Ricardian trade model, see Alder (2016); Asturias et al. (2015). For ecological outcomes, see Asher et al. (2019).

out that their OLS estimates may be affected by the fact that the route of the highway may have been chosen to connect regions that were (a) expected to develop or attract businesses, or (b) were struggling and needed investments to turn them around, or (c) had other systematic differences like lesser land acquisition issues, and therefore less agricultural regions. My paper is, therefore, complementary to the Ghani et al. (2015) work. Firstly, while their paper analyzes how manufacturing firms respond to upgrades, I estimate the effects of historical connectivity on *overall* economic activity associated with night-time lights. Secondly, since the highway project updated an already existing network of different forms of transportation, unlike the Ghani et al. (2015) paper, my paper focuses on the long-run economic impacts of being connected to these historical transportation networks, and the eventual dispersion and dissipation of these impacts. Our results together suggest that organized manufacturing responded differently to upgrades than other economic activity. Importantly, I study and quantify the extent of neighborhood spillovers and show how they affect the rates of convergence in incomes across regions by formalizing regional development in a growth-model framework.

Within the Indian context, other work studies the historical expansion of railroads (Donaldson, 2014) to look at price equalization and regional development, or more recent low-cost rural road construction programs (Asher and Novosad, 2016) to look at village employment. Papers on highway infrastructure in the US context (Atack et al., 2008; Donaldson and Hornbeck, 2015; Michaels, 2008) look at market access, urbanization, population movements and the demand for skill across different regions. Indeed, such structural models of market access do an excellent job of quantifying the general equilibrium effects via changes in prices. Last, while the literature on neighborhood spillovers in economic activity is scant, there is a growing literature on Solow (1956)-style convergence within countries (for an analysis of US counties see Higgins et al. (2006)) which my paper addresses by estimating the rate of convergence across regions driven by these regional externalities.

3 Data and Sample

The primary dependent variable of interest is night-time lights as measured by satellite imagery. This has been used as an indicator for economic development, especially in developing countries that have issues with disaggregated income data (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013). In a similar fashion to me, Storeygard (2016) uses a panel of night-lights among sub-Saharan African cities to study urbanization among routes connected to ports. Researchers at the National Oceanic and Atmospheric Administrations (NOAA) National Geophysical Data Center (NGDC) process data from weather satellites that circle the Earth 14 times a day and take pictures between 2030 and 2200 hours at night. They use algorithms to filter out other sources of natural light using information about the lunar cycles, sunset times and the northern lights, and other occurrences like forest fires and cloud cover. Given a lack of reliable sub-regional level GDP data in India, this measure is ideal to capture overall economic activity.

Figure 1a zooms in on the region connecting Delhi-Mumbai and Delhi-Kolkata where a stream of lights is associated with the National Highway that connects the nodal cities, whereas Appendix Figure A7 shows the entire geographic distribution of night-time lights along with the straight-lines between the four nodal cities. The Golden Quadrilateral Highways and the sub-districts used in the analysis are shown in Figure 2. I calculate great-circle distance to the nearest straight line, and in some specifications I use data on actual highways and roads that are obtained from the Digital Chart of the World (DCW) database. DCW provides detailed information on road and rail routes based on the content in the US Defense Mapping Agency (DMA).

The lights data is calculated at approximately every one square kilometer, but I aggregate the results to the sub-district level in order to account for issues of spatial correlation.[10] I regress this lights data on distance to the nearest straight line connecting the nodal cities.[11] Epanechnikov kernel density plots of light density over time in Figure 1b show that as the country grows between 1992 and 2002 there is an increase in mean light density and a reduction in the variance, yet this is not true of the following growth decade.

In all calculations, I drop the nodal cities and 26 adjacent sub-districts so as to not capture the impact of being a neighbor to a big city. I include year fixed effects to capture the change in average light density due to changes in satellites across years. In all specifications, I flexibly control for other geographic features like distance to closest nodal city, coastline, latitude and longitude. I perform robustness checks that drop outlying areas, islands and areas far from the national highways.

3.1 The Elasticity between Light Density and Domestic Product

In order to get at spatial development at a finer level, this paper studies the impacts at the administrative level of the 2253 sub-districts. Gross Domestic Product (GDP) is not calculated at this level, but there are GDP numbers available for about half the 594 districts in the country, and for all the 32 states. The elasticity between State Domestic Product (SDP) and light-density will be an underestimate of the true elasticity between sub-district domestic product and light-density because of the measurement error introduced in aggregating the 2253 sub-districts into 32 states. The relationship between District Domestic Product (DDP) and light-density, while suffering from some measurement error as well, will however bring us closer

[10] Sub-districts are the third largest administrative unit of aggregation with a population of about 460,000 people on average. Results will be presented with standard errors clustered at even higher levels of aggregation. There are 2253 sub districts in 594 districts which are in 35 states and union territories. Results are statistically significant even at standard errors clustered at the level of 35 states.

[11] Following the conventions established in the literature (Michalopoulos and Papaioannou, 2013), the lights data is transformed to be of the form: $Log(0.01 + Luminosity)$ to account for the fact that some areas have no luminosity. About 1.6% of the total sample, and less than 1% of the last 3 years of the sample have sub-districts that had no luminosity. Furthermore, the results are robust to using Poisson regression specifications of luminosity, and an inverse hyperbolic sine transformation. I also present results of $Log(Luminosity)$ for the regions that never have 0 recorded lights – an impact on purely the intensive margin.

to the true parameter. Appendix Tables A5 and A6 show the state-level and district-level elasticities between GDP and luminosity. While the state-level elasticities are a little below 0.2, the district-level elasticities are a little above 0.3 in general, and there is no trend over time in the elasticities. Due to measurement error in aggregating lights and domestic product to a higher administrative unit, the true sub-district level elasticities should be higher. The cross-country literature (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013) has elasticities of about 0.3 for sub-samples of low and middle income countries, suggesting that 0.3 would be a reasonable lower bound for the sub-district level elasticities.

4 Historical Connectivity to Transit Networks

In this section, I study the effect of being close to transit networks that have historically existed for many decades, and in the following section, I see how this long-run relationship is changing over time. These two sections characterize the reduced form impacts of roads. In Section 6, I parameterize these relationships in order to estimate the overall impacts of these routes in the presence of regional externalities.

4.1 Empirical Strategy

While the actual path of these routes is endogenous to regional characteristics, being on a straight-line between two major cities should not be correlated with anything other than being close to the routes connecting them. In order to examine the long-term general impact of connectivity to historically determined transportation networks, I look at the impact on lights for sub-district i closer to the straight-lines using the following regression specification:

$$LogLights_i = \alpha_i + \gamma \mathbf{X} + \beta Distance_i + \epsilon_i \tag{1}$$

Equation (1) is the reduced form specification where $Distance_i$ is the distance between the sub-district and the nearest straight line, and $\mathbf{X}$ are geographic controls (distance to nearest nodal city, coastline, latitude and longitude).[12] To obtain the OLS estimator, I replace the $Distance_i$ variable with distance to the nearest highway, or distance to the nearest rail-line. The OLS estimates, however, will be biased as highways and rail-lines will be laid according to where cities and economic centers are located, or lagging regions where the government wishes to induce economic activity. It is interesting, however, to study the direction of the bias. If road and rail-lines are laid to be closer to economic centers, then the estimates will show large impacts of being close to a highway or rail-line. If, however, land acquisition for construction

[12] Some results are presented as distance in kms to be comparable to the Ghani et al. (2015) paper, and other results are presented as Log(distance) to calculate the elasticity as in the Banerjee et al. (2012) paper.

of rail-lines and roads forces the government to move away from economic centers, then the impact of distance to these lines would be attenuated.

Finally, one can derive the upper-bound of the effect of roads and rail lines by performing a two-staged least squares exercise of the following form:

$$\begin{aligned} DistanceToRoad_i &= \pi Distance_i + \mu_i \\ LogLights_i &= \alpha_i + \delta_i + \gamma \mathbf{X} + \beta \widehat{DistanceToRoad}_i + \epsilon_i \end{aligned} \tag{2}$$

For distance to the line to be a valid instrument, it must be that regions along these straight-lines do not systematically have a different light-density for any reason unrelated to road or rail routes. Since the impact of the distance to the straight-lines will work through both rail lines and roads, distance is not an instrument for each separately, but rather an instrument for transit networks in general. It is, however, possible to see the strength of the instrument for roads and railways separately. I find that the straight-lines are strong predictors of highway placement, but not for rail lines, suggesting that the effects I capture are more likely to be driven by these highways. Later, I isolate the impact of upgrading the highway system by comparing districts close to and far away from the straight-lines, before and after the highways were upgraded.

Table 1 shows the relationship between distance to the straight-lines and distance to transit networks. While the distance to the straight-line is a good predictor of distance to the nearest GQ highway, it only does moderately well in predicting distance to the closest rail line. This is hardly surprising, as GQ highways were built in order to connect the nodal cities, while rail lines were built to connect other cities as well. Throughout the paper, the results will be clustered at higher-level administrative units like districts or states in order to account for spatial correlation and for correlations in outcomes within administrative units.

4.2 Results: Distance to GQ Highway and Railways

The OLS, reduced form and 2SLS estimates between light-density and proximity to the nearest GQ highway are shown in Table 2 for every decade – the years 1992, 2002 and 2012. In 1992, the OLS estimate had a coefficient of -0.391. Since the distance variables are in 100km, this means that a 100 km increase in distance from the highway was associated with a fall in light-density of 0.391 log points. As discussed previously, a reasonable lower-bound for the elasticity between sub-district domestic product and lights is 0.3; in the literature, a 1 log point increase in light density is usually related to the a 0.3 log point increase in income for the sample of low and middle income countries (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013). Therefore, a 100 km increase in distance from the highway would be correlated with a 12% fall in income. By the year 2012, this had halved to about a 6% difference in income.

The most commonly used metric for luminosity as a predictor of development is the light-density variable (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013). In Table A2, I present the OLS estimates of the relationship between distance and *other* measures of night-time lights, including the standard deviation of lights within a sub-district. In order to look at the extensive margin, the last column in Table A2 is a linear probability model (LPM) of the probability of having the majority of recorded light-emission pixels in a sub-district be greater than 0. This relationship is greater in 1992, again suggesting that over the two decades the relationship between distance to the highway and development has weakened.

The second column of Table 2 shows the reduced-form relationship between lights and the distance to the straight-lines that connect the nodal cities. Once again, the relationship is much larger in magnitudes in 1992 than in 2012, and of similar size as the OLS estimates. Similarly, Table A3 shows the analogous reduced form relationship for other measures of night-time lights and distance to the straight-line.

The two-staged least squares (2SLS) estimates are presented in the final column of Table 2 (and Table A4 shows the corresponding relationship for other measures of lights).[13] In Table 1 the excluded distance-to-line variable has a high F-stat no matter what the level of clustering, displaying a strong first-stage relationship. The 2SLS estimates are slightly more negative than the OLS estimates in some cases – for instance, in 1992, the 2SLS results say that a 100km increase in distance from the highway leads to a 0.5 log point fall in light density. Assuming the same elasticity between lights and income, this is a 0.15 log point or about a 16% fall in income. The 2012 light-density coefficient, however, is identical to the OLS result.[14]

In Table 3, I estimate the elasticity between distance and economic activity over time. By using a log-log specification in each year, I calculate how this elasticity between lights and distance to the nearest straight line is changing between 1992 and 2012. Given that a lower bound for the elasticity between lights and GDP per capita is constant at 0.3, the results indicate that the elasticity between GDP per capita and distance is falling over this period from about 0.15 to 0.06. The range subsumes the Banerjee et al. (2012) elasticity of 0.07, but for much of the period is higher. The results therefore indicate that in 1992 this elasticity was high, and that historical connectivity played a large role in regional and spatial development. However, this elasticity more than halves to fall to an economically insignificant relationship by the end of the period. If we merely estimated the impact in 2012 we may wrongly conclude that transit networks do not strongly affect incomes.

This dissipation of the impacts has not been investigated in the literature, and is studied below in Section 5 in more detail, where large spatial spillovers can lead to a dissipation in the differential increases in income for the regions along these routes.

[13]We can think of the 2SLS estimates capturing the effect on the regions who were induced into building by lying on the straight-line path between two metros.

[14]Tables A7 and A8 show the analogous OLS and 2SLS results for distance to the nearest railway line. As the distance to the straight line is only a moderately good predictor of distance to the rail line, the bulk of the reduced-form impact is coming via roads. For rail lines, we can see that the 2SLS results are much larger than the OLS results. The reduced form is in Table A3, and the 2SLS results are magnified by the fact that the excluded distance-to-line variable is a poor predictor of the distance to nearest railway line.

5 Dynamics and Changes Over Time

In this section, I examine the dynamics of this dissipation in more detail. I focus on how the economic impacts of these routes change over time, and the effect of the major highway upgrading program which took place between 1998 and 2006. First, I estimate the following regression for sub-district i in year t:

$$LogLights_{it} = \alpha + \delta_i + \tau_t + \gamma \mathbf{X} + \beta_{\mathbf{t}} \left(Distance_i \times \tau_t \right) + \epsilon_{it} \tag{3}$$

The regression includes year fixed effects τ_t, region fixed effects δ_i and the usual geographic controls $\mathbf{X}$, similar to a multi-period difference-in-differences specification. The coefficient of interest $\beta_{\mathbf{t}}$ is on the interaction term between $Distance_i$ and τ_t. In the regressions, the omitted year is the first year of the sample – 1992.

Figures 4b plots $\beta_{\mathbf{t}}$ to show how the effect of distance on light-density changes relative to 1992. Positive values of $\beta_{\mathbf{t}}$ indicate that the impact of distance on lights is falling relative to 1992. In the figures it is clear that this differential impact is indeed falling over time, especially after the upgrades to the highways system begins in 1998. It is however, not possible to reject the possibility that the dissipation of the relationship between distance and development would not have happened if the highways were not upgraded.

Appendix Figure A10 shows this relationship for different measures of night-time lights and finds similar trends over time – the impact of being far away from these routes decreases over time. The panel on the standard-deviation of lights shows that even though inequality within a sub-district was higher for regions closer to these routes, this difference has been shrinking over time. Robustness to different specifications is shown in Appendix Figures A12. The figure has four panels allowing for two different levels of clustering errors and doing robustness checks with dropping any sub-district that ever had zero recorded luminosity, and dropping any subdistrict that ever had any pixel with the maximum possible luminosity value. Appendix Figures A11 reproduces the main results after excluding regions that are a significant distance away from these routes.[15]

Table 3 shows the 'reduced form' elasticities between light and distance to the straight-line, and in Figure A8 I show the OLS and 2SLS elasticities over time. While the elasticities are similar towards the end of the period, there are stark differences in the beginning of the period. One explanation for this convergence, is that in the early 1990s, the 'distance to line' could be picking up other transit networks as well in the 2SLS regression, but by the 2000s the highways seem to become the dominant channel. And this shift in importance of which transportation networks are used may be due to the highway upgrades.

[15]The excluded regions include the states of Jammu and Kashmir, Sikkim, Assam, Arunachal Pradesh, Meghalaya, Mizoram, Tripura, Nagaland, Andaman and Nicobar Islands and Lakshwadeep.

5.1 Upgrading the Highways

The literature on the golden quadrilateral (Ghani et al., 2015), has so far concentrated on the upgrades that were started in the late 1990s. The NHDP upgrading projects were first finalized in 1998, and the foundation stone was laid by the Prime Minister on January 6, 1999. The first couple of years, however, were plagued with delays in certain areas because of contractual issues and problems with land acquisition. About 20% of the projects started between 1998 and 2000, whereas almost 50% of projects started in 2001.[16] While Phase I of this project officially ended in 2006, about 8% of the projects ended a few years later. Later phases added some additional upgrades, and work continued on the GQ till the end of 2011. This timing allows for a before-after analysis of this highway upgrading, since the lights data spans from 1992 to 2012. The period 1999 to 2006 in the sample will be considered to be the 'upgrading' phase, while the years after that will be the post-project phase. In order to see how the impact of distance changes with time, I estimate the following specification:

$$LogLights_{it} = \tau_t + \beta\mathbf{X} + \delta_1 Distance_i + \delta_2 \left(Distance_i \times Construction_t\right) + \delta_3 \left(Distance_i \times Post_t\right) + \epsilon_{it} \tag{4}$$

Here δ_1 is the impact of distance on lights in the pre- upgrading period, $\delta_1 + \delta_2$ is the impact in the upgrading period, and $\delta_1 + \delta_3$ is the effect in the post-upgrading period.

Table 4 shows the impact of distance over these three periods. In the pre-upgrading period, light density would fall by 3.4 log points for every increase in 1000km from the straight line, but once upgrading starts, this falls by 1 log point to about 2.4 log points, and in the post-upgrading period it's even lower at about 2 log points. All measures are statistically different from zero, and show that the impact of highways on development $falls$ around the turn of the century, after the highway upgrading begins. If the upgrades made the highways more important, then we should expect the opposite result – that they should matter more for economic activity. This does not necessarily indicate that the highway construction *caused* the relationship to dissipate, as the relationship was already weakening over time. If anything, upgrading the highways did not change the rate at which this relationship was weakening over time.

To see at what distances the change in impact appears, I split up all positive distances into 8 equal quintile indicators $\Psi_q = 1$ if the region lies in distance quintile q. I interact these with indicators for being in the construction phase or the post-project phase. In the regression equation below τ_t are year fixed effects and $\mathbf{X}$ is a vector of geographic controls:

$$LogLights_{it} = \tau_t + \beta\mathbf{X} + \sum_q \left(\psi_{\mathbf{1q}}\mathbf{\Psi_q}\right) + \sum_q \left(\psi_{\mathbf{2q}}\mathbf{\Psi_q} \times Construction_t\right) + \sum_q \left(\psi_{\mathbf{3q}}\mathbf{\Psi_q} \times Post_t\right) + \epsilon_{it} \tag{5}$$

The omitted category in this regression are the sub-districts that are on the straight-line (5% of all sub-districts). $\psi_{\mathbf{1}}$ traces out the impact of distance from these sub-districts in the pre-

[16] Source: National Highways Authority of India http://www.nhai.org/completed.asp

upgrading period, whereas $\psi_1 + \psi_2$ is the impact during the upgrading phase. These coefficients can be plotted for each distance quantile to look at the semi-parametric impact of distance, and how the impact of distance changes across the three time periods.

The lines in Figure 4a show the impact on light-density by distance quantiles, relative to sub-districts that lie on the straight-lines. The blue lines are for the pre-upgrading period, the orange for the upgrading period, and the green lines are for when the project is over. Looking at the pre-upgrading period in panel (b), we can see that a district in the eighth distance quantile has about 2 log points less light density than a district that is on the line. But once upgrading begins, these lines start flattening out. Together these results suggest that while an increase in distance from the straight line leads to less development, this relationship weakens in the later period, and especially after the upgrading of the highway.

Figure A11 reproduces this result for other measures of light-density. The panel on the standard-deviation of lights in Figure A11 shows that there is a larger dispersion of lights within a region that is closer to the route. This gives us some indication towards the pattern of development in these regions – that in sub-districts near the route there are a few large towns with a lot of activity, and then areas with very little activity. In regions away from the route however, there is an equal amount of low economic activity. This pattern is consistent with developed regions reflecting agglomeration economies, where activity is concentrated in certain areas but is sparse in other regions Krugman (1991).

Ghani et al. (2015), show that upgrading the highways induced new manufacturing firms to enter in regions close to the highway. The difference in our results are not due to the methodology, and are likely due to different outcome variables.[17] Their paper looks at the organized manufacturing sector, for about half the districts in the country, and shows that there was an increase in entry for such firms in regions within 10kms of the highway.[18] Together our papers, therefore show that while there was an increase in the entry of organized manufacturing enterprises, overall economic activity was still shifting away from the highways.[19]

This spread in economic activity may have been stemmed if upgrading the highways induced enterprises to stay or enter in regions on the highway at a higher rate than other regions, as with for firms in the organized manufacturing sector. There is, however, little evidence in this paper to show that upgrading the highway system actually turned around the trends that were already visible in the data for overall economic activity.

[17] While Ghani et al. (2015) use an OLS specification for their main results, they show robustness to using an IV approach. Unlike this paper, instead of using a continuous "distance" measure, they use two discrete categories – compare districts between 0 and 10km near the road to districts further away with a 1/0 indicator for whether you are within 10kms of the highway. When I use their methodology, I still find that the relationship between night-lights and distance to the road dissipates over time.

[18] Their sample is only for states that had enough manufacturing activity, and in districts that were observed over their entire panel.

[19] One possibility that Ghani et al. (2015) mention in relation to my work is the change in the composition of economic activity – for instance, organized manufacturing firms may move closer to the highway, but other firms may not.

One way to finally determine whether the GQ upgrades caused these trends is to look at another route that did not have heavy investments in the highway system: the diagonal of the quadrilateral between Mumbai and Kolkata. Table 6 shows that the elasticity between economic activity and distance to a straight line connecting these two cities, which is less than one-third the size than the elasticity along the sides of the golden quadrilateral. Yet, the elasticity has been dissipating over time, despite the fact that there were no projects under the National Highway Authority of India to upgrade the routes between these two cities. If this is an indication of the trends seen along routes connecting the other nodal cities, then the upgrading of the highway may not have had much of an impact on the pre-existing trends under which economic activity was already spreading geographically away from the well developed regions. These mechanisms are explored further when studying the geographic spillovers within the confines of a modified neoclassical growth model that I set-up in Section 6.

5.2 The Nature of (Spatial) Development

While light-density may be a good proxy for overall economic activity, it tells us little about the nature of this economic activity. GDP data in India is scant, unreliable and not harmonized across regions. I collect district level GDP data from each state's statistical agency, when available. There are no data for sub-district level GDP. The years 2000 to 2005 provide the longest consistent balanced panel of such districts. In Table A1, I present the results on the impact of distance to the line on district GDP. A 100 km increase in distance reduces GDP by 0.13 log points in 2005.

Unfortunately, the only source of data that provides counts at the sub-district level is the Census of India which has a limited number of outcome variables and is only compiled once every 10 years. Table 8 shows results from the 2001 and 2011 Censuses. While regions further away from the route have less population overall, they have a higher concentration of Scheduled Tribe (ST) persons. Along with the Scheduled Castes (SCs) these are among the most socio-economically disadvantaged groups in the country. Furthermore, regions further away also have a higher concentration of cultivators, but lower concentration of persons engaged in household industry. While distant regions also have lower literacy rates, they have a more equitable distribution of literacy across genders – the gender-gap defined as the difference in the male and female literacy rates is lower. Unfortunately, without more detailed data at the sub-district level, it is hard to discern any intricate patterns in the nature of economic activity, but it is clear that regions farther away from the route have a higher concentration of marginalized populations, lower literacy, and have more cultivators but less persons engaged in household enterprises.

The question of what kind of economic activity the night-lights are picking up over the long-run will provide more information on the nature of development. If the regions further away from the routes were previously uninhabited and the routes allowed people to locate there, then we should see a rise in population for those regions. If, however, it is merely the composition of the population and the kind of economic activity undertaken by them, then for a given population, the increase in night-lights will represent more wealth per capita being generated.

To get at the question of whether there are population changes to less inhabited regions or whether the changes over time are picking up increases in economic activity per capita, I use the LandScan data on population estimates. The data compiled by the US Department of Energy's Oak Ridge National Laboratory, uses sub-national Census counts and primary geospatial ancillary datasets, including land cover, roads, slope, urban areas, village locations, and high resolution imagery analysis of settlements, to predict the populations at a finer geographic level than available elsewhere.

Table 5 presents the elasticity between population and distance to the nearest straight-line connecting nodal cities over time (starting when the data begins in 2002). While the elasticity is high (between 0.18-0.2) for this period, there is no change in the elasticity over time. This shows that the change in the night-lights elasticity over time is driven by something other than the number of people migrating to newer areas, and instead is due to changes in *per-capita* economic activity.

5.3 The Spread of Peripheral Roads

Construction of National Highways may facilitate the spread of economic activity by now promoting the construction of peripheral highways and roads. State governments are often in charge of the construction of these roads. I collect data on highway-density of both national highways and state highways to study whether the GQ highways facilitates the spread of other highways from its nodes. In Table A9, I present these results. While there is little evidence that the GQ facilitated the construction of other national highways, it is clear that state highways could now use the GQ to increase connectivity to other regions. The construction of these state highways may then facilitate the spread of economic activity to interior regions as well.

6 A Simple Model of Spatial Development

Better access to transportation networks can induce development in connected regions by facilitating trade and migration, the spread of technology and ideas, and reducing price volatility. So far from the results it is clear that until the early 1990s, being near the transit network that connects the four major cities had statistically and substantially significant impacts on regional development. However, the impact of being close to the straight lines dissipates over time, even after the highway system is upgraded. Why, then, does the effect of the transit network dissipate? One possibility is that these routes affect the initial level of development more than the steady state level – in such a situation, a simple neoclassical growth model would predict that underdeveloped regions would grow faster and there would be convergence in incomes across regions. In such a model, the dissipation has nothing to do with spillovers. If we build in the possibility of spillovers in economic activity across regions, this not only spurs the growth in underdeveloped regions but also increases the overall impact of these routes. As I will show with my structural estimates, the evidence strongly supports a model in which there are economic spillovers in activity across neighboring regions.

6.1 Distance to the Network and Neoclassical Growth

First, let us consider the model that is not driven by spillovers. While transit networks may be important for regional development, these impacts may dissipate over time on their own. After the four nodal cities were established, the regions that had the least-cost connections to these cities started developing. This helped build up a network structure whereby regions connected to these growing regions started growing. Since regions connected to the routes started growing earlier, they are at any point of time closer to their steady-state level of development than regions further away which will hence be growing faster. If we then look at long-term development, the first set of regions would have more economic activity, but their neighbors and their neighbors' neighbors would be catching up over time. This would then produce the dynamic trends seen in the data, and is consistent with the results found in Banerjee et al. (2012), where they find that Chinese regions near the straight-lines had reached a slightly higher level of income, but were not necessarily growing faster than other regions.

There are a few ways to incorporate transit networks into a Solow (1956)-style growth model. One possibility is that distance to networks affects the steady-state level of development, which would then predict regions closer to the highways would grow to a higher level of income than regions further away. Another possibility is that the distance to transit networks only affects the initial level of income, and all regions converge to a similar steady-state level of economic activity. This would then be consistent with a result that shows that regions further away from the route have higher growth rates. To formalize this framework, we can modify the empirical predictions of the neoclassical growth model in the following way:

Let y_{td} be income per effective worker in sub-district d and time t. A region on the route is a simple Solow-style economy with income $\bar{y}_t$. A region that is distance D from the route can be characterized in relation to the region on the network:

$$y_{td} = D^{\alpha_t} \bar{y}_t \tag{6}$$

Here $-1 < \alpha_t < 0$ captures the elasticity of income with respect to distance from the route. This framework is similar to gravity-models in trade theory, where the distance would be picking up trade-costs and other frictions. Given that the evidence so far shows that this elasticity is higher in earlier years, α_t can be simply represented by:

$$\alpha_t = \lambda + \frac{\psi}{(1+t)} \tag{7}$$

Here $-1 < \lambda < 0$ captures how distance to the transit network affects the steady-state level of income, and $\lambda + \psi$ the initial level of income. One test is to see whether these routes have a larger effect on the initial level of income or the steady state level. If, and only if, the routes affect the initial levels of income more than the steady state levels, then $\psi < 0$ as well, and we should see that regions further away from the route grow faster. From the results in Table 3 it is clear that $\lambda + \psi < -0.497$ and $\lambda > -0.212$. Together, this implies that $\psi < -0.285$.[20]

6.2 Convergence

In the results so far, we see that while regions along the route are richer, there is a catching-up of regions further away. The Solow (1956) model's predictions of a conditional (on parameters) convergence of per-capita incomes may be used as a framework to study these patterns in the data. Barro and Sala-i Martin (1992) are careful to distinguish between the different notions of convergence. If $\beta-$convergence holds then poorer sub-districts would be growing faster than their richer counterparts. The Neoclassical growth framework has certain predictions for the rate of convergence to steady state β. As discussed in Barro and Sala-i Martin (1992, 2004) and Mankiw et al. (1992), the solution to the income dynamics can be characterized by:

$$log\ y_{td} = (1 - e^{-\beta t})log\ y^*_d + e^{-\beta t}log\ y_{d0} \quad , \tag{8}$$

where y_{d0} represents the initial level of income, and y^*_d the steady-state level in district d. Given this setup, there are a few ways to then estimate the rate of convergence. One possible approach is to use a cross-sectional regression based on the long difference between the first and last year in the data, as explained by Mankiw et al. (1992):

$$log\ y_{td} - log\ y_{d0} = \gamma_0 + (1 - e^{-\beta t})log\ y_{d0} + \gamma_x \mathbf{X} + u_{dt} \tag{9}$$

β can be estimated from the coefficient on initial income. Another approach was used by Evans (1997) and Higgins et al. (2006) amongst others. Here, instead of using the cross-section, they use all the years and back out the rate of the convergence:

$$growth_d = \delta_0 + \delta_y log\ y_{d0} + \delta_x \mathbf{X} + u_{dt} \tag{10}$$

[20] These estimates are bounds, rather than precise estimates since we neither observe year 0 nor the steady-state, which lies in the perhaps distant future. If we assume that 1992 is the 'initial' period, or that the steady state has been reached by 2012, then $\lambda = -0.212$ and $\psi = -0.285$.

Here, $growth_d$ is the average growth rate across all the years for a region d. The rate of convergence over T periods is then simply $\hat{\beta} = 1 - (1 + \hat{\delta}_y T)^{\frac{1}{T}}$.

In Table 7, I present results using both methods. The Mankiw et al. (1992) cross-sectional method shows a convergence rate of 4% a year, whereas the Evans (1997) and Higgins et al. (2006) method displays a rate of 3.9% a year. These are both double the 2% rate that we see in cross-country convergence rates (Sala-i Martin, 1996). While capital mobility within the country can aid rapid convergence, labor mobility in India is low (Munshi and Rosenzweig, 2016). Rates of convergence could be higher within countries due to spillovers in economic activity across regions, amplified by the movement of capital, technology or workers.

Lastly, $\beta-$convergence is a necessary but not a sufficient condition for a decrease in the variance of incomes across regions, also known as $\sigma-$convergence (Barro and Sala-i Martin, 1992). Figure 1b shows that between 1992 and 2002 the variance in light density shrank a lot, but this did not continue for the next decade.

6.3 Spillovers and the Direction of the Spread of Development

While the Solow-style model discussed in Section 6.1 is consistent with the dynamic trends, it says nothing about spillovers in economic activity across regions. It does not necessarily predict that as one region gets richer that will *lead* to its neighboring regions getting wealthier as well over time. In this section I explicitly show strong evidence of such spillovers, and estimate the parameters of a simple model that will help quantify the extent of these spillovers and the overall benefits of these routes. In such a model, distance to the highway not only directly affects the income levels (as in the Neoclassical growth framework) but also sets into motion certain dynamics that affect the spatial development of neighboring regions as well.

As a descriptive exercise, in Figure 3 I follow the regions around the Mumbai-Chennai highway over time. The pictures show the regions along the highway (depicted by a blue line) and along the straight-line path (red line) every 5 years, on a Green to Red spectrum (where deeper green reflects less economic activity, and red indicates more activity). It is clear that early developers are the ones along the route, after which economic activity fans out to neighboring areas, and then to the neighbors' neighbors, eventually reaching areas even farther away.

If economic activity spreads from regions close to highways to regions away from the highway, then a given region (d) should be affected more by economic activity in neighboring regions that are closer to the highway ($d-1$) than neighboring regions that are further away from the highway ($d+1$). Let $Log\ y_{td}$ be income in region d at time t, $Log\ y_{t,d-1}$ be the mean light density for all its neighboring regions that are closer to the highway, and $Log\ y_{t,d+1}$ be the mean light density for neighboring regions farther away from the highway. In the regression below, we should then expect $\delta > \gamma > 0$ if economic activity is spreading from regions closer to the highway to regions away:

$$Log\ y_{td} = \alpha_d + \delta Log\ y_{t,d-1} + \gamma Log\ y_{t,d+1} + \epsilon_{td} \tag{11}$$

While this regression formulation shows a contemporaneous impact, the effect could also have a period lag, when activity in a region today can affect economic activity in a neighboring region tomorrow. Furthermore, the true relationship could be one of changes, where changes in a region's economic activity affect changes in its neighbor's activity. It is important to stress however, that the true test of the model is one where $\delta > \gamma$, and not merely if $\delta > 0$, since $\delta > 0$ is also consistent with a model of spatial correlation in income shocks. The regressions for contemporaneous spillover effects, as well as the one-period lagged effect and the changes over time specification are shown in Table 9, where it can be seen that δ is always statistically and economically significantly greater than γ.

Studying the pattern of lights in regions along the route, and their neighbors would help answer the question of how spillovers are leading to convergence. In order to study this, let us define a 'degree-of-separation' (s) as how many regions lie between your region and the route. For example, $s = 1$ means the region neighbors a sub-district that lies on the route, and $s = 3$ means that the region is a neighbor of a neighbor of a neighbor of a region, that lies on the route. Plotting the coefficients (β_{st}) of the regression below for each s and over time t, allows us to study whether convergence takes place across neighboring regions. In the specification below, $\mathbf{1}_{s=S}$ is an indicator function that depends on the 'degree of separation' of the given region, and $Year_t$ is an indicator variable for the year:

$$Log(Light\ Density)_{dst} = \alpha + \sum_s \beta_{st} \left(\mathbf{1}_{s=S} \times Year_t\right) + \epsilon_{dt} \tag{12}$$

In Figure 5 each point is the differential impact of light density on that region compared to other regions in a given year. It can be seen that regions on the straight-line connecting two major cities have the highest light-density compared to other regions, and the regions that are one-degree of separation away are only slightly worse off. Figure 5, therefore, indicates a few things. First, the ordering in term of 'degrees of separation' is maintained, whereby regions closer to the route have higher light-density, and even though there is convergence over time, we don't see an 'over-taking' by the regions further away. Second, while it seems like the 1990s were a period where convergence was rapid, this has slowed down in the later half of the 2000s. At the end of the period, regions still maintain their initial ordering in concentration of light-density, an ordering which directly depends on their 'degree-of-separation' from the route. Third, it is clear that distance to the route strongly affects initial income levels, as seen by the dispersion in incomes in the first year of the data. Last, distance to the route also affects the steady state level of incomes, as the same ordering remains in the last year of the data despite a slowdown in the rate of convergence in the last few years.

6.4 Testing the Model and Estimating Spillover Parameters

A strong test for the importance of these spillovers is to see how a structural model of the spillovers correctly predicts the reduced form impacts of the routes in each year. To formalize this, let y_{tk} represent income in region d and $y_{t,d-1}$ be the mean income for all its neighbors that are closer to the route than region d. For a given distance from the route D_d, let the true relationship between income and distance be a modification of equation (6):

$$y_{td} = (D^{\mu_t} \bar{y}_t)\, y_{t,d-1}^{\chi} \tag{13}$$

$0 < \chi < 1$ represents the neighborhood spillover effect of economic activity from bordering regions closer to the highways, and $-1 < \mu_t < 0$ represents the direct effect of being further away from these routes. This equation can be solved forward recursively to:

$$\begin{aligned} Log\ y_{td} &= \left(\sum_{j=0}^{d} \chi^j\right) \mu_t Log\ D_d + Log\ \bar{y}_t & (14)\\ &\equiv \alpha_t Log\ D_d + Log\ \bar{y}_t & (15)\end{aligned}$$

We therefore recover equation (6), showing that the model with spillovers is a general form of the model without. Equations (14) and (15) can be used to estimate parameters χ,μ_t and α_t, and we can test the following model prediction is true in a stringent validation exercise:

$$\alpha_t = \left(\sum_{j=0}^{d} \chi_t^j\right) \mu \tag{16}$$

Table 10 shows results for both Equations (14) and (15).[21] The distance-spillover parameter $\left(\sum_{j=0}^{d} \chi_d^j\right) \mu$ according to equation (13) is also presented, and is almost identical to α_t as seen in equation (14). This is a strong test of the model that neighborhood spillovers across regions exist in this context, and drive income convergence. The spillover parameter χ is relatively stable over time and lies within the range of 0.77 and 0.868, whereas the direct-distance effect μ_t is initially -0.104 and falls to about -0.064. The distance-spillover parameter $\alpha_t = \left(\sum_{j=0}^{d} \chi_t^j\right) \mu$ is initially 0.5 and halves to about 0.25 by 2012. All these parameter estimates are statistically indistinguishable from 0 in all years.

Figure 6 shows how well the model fits the data by plotting both the reduced form elasticity of light-density with respect to distance, and the corresponding structural-parameter-based prediction of this elasticity from a model that incorporates these spillovers. The model fit validation is good throughout the period, lending strong credibility to the structural assumptions.

Finally, how this relationship changes over time tells us about how these spillovers can actually lead to convergence across regions. In the cross-country version of the Solow (1956) model, the

[21] For this test, we need to use the fact that on average regions have about five to six degrees of separation between the route and themselves (i.e. d is approximately six).

convergence across regions could be generated without any spillovers, and often leads to rates of $\beta-$convergence of about 2% (Sala-i Martin, 1996). Within a country, however, spillovers across regions can speed up convergence, and generate rates like 6% for US counties (Higgins et al., 2006), or 4% as in the case of this paper.

6.5 Income Elasticities with Spillovers

The structural estimates together then allow us to back out the income elasticities with respect to distance from these routes, after accounting for the presence of these spillovers. To reiterate, ignoring the presence of (positive) spillovers underestimates the true effect of these routes. The issue here is that when comparing a region on the route to a neighboring region, by ignoring the spillover we are subtracting it from the overall effect of the route, when in fact we should be adding these spillovers to the total impact.

At the bottom of Table 10, I present the income elasticity ignoring the spillovers and the elasticities taking them into account. In 2012, if we ignore the spillovers in our calculations, we would have estimated an elasticity of 0.06 – a small number, suggesting that investments in transit networks may have low returns. Taking the spillovers into account raises the income effects of routes by more than three times to 0.21. If we ignored spillovers we would say that a 10% decrease in distance from the route, raises incomes by only 0.6%, but incorporating spillovers, we can see that *overall* incomes rise by 2.1% – a substantial amount by many measures.

In Appendix B, I explore the mobility of capital and labor to see whether standard models and evidence can pin down how they contribute to this spread of economic activity over time.

7 Conclusion

The impact of transportation infrastructure on regional development has long been debated. In general, better transit networks have been thought to facilitate trade, migration, the spread of ideas and technology, credit and other financial opportunities, and decrease price differentials and volatility. Studying infrastructure projects in different contexts have however provided contradictory evidence. Fogel's (1964) study of US historical development argues that there were limited impacts of railways on growth relative to the transportation networks that used waterways, whereas Hirschman's (1969) treatise posits that social overhead capital, like railways, have significant linkages that promote growth in industries. For Hirschman (1969), infrastructure projects would have forward linkages (promote industries that need roads and railways), backward linkages (promote industries that supply materials for road and rail construction) and lateral linkages (connect industries together). The Fogelian view, on the other hand, supports the idea that much of US historical investment in railways was misguided and therefore did not have impacts on development because of governmental policies that subsidized railway construction. The natural experiment under analysis in the Indian context, however, is that some regions happened to be on the path of shortest distance connecting major centers of economic activity, and we are hence less likely to find 'misguided' investments in this context.

The results in this paper indicate that while distance to the straight line may have substantial impacts on regional development till the early 1990s, the strength of this relationship dies out slowly over the next two decades. If one was to analyze the relationship at the end of this period, they would come to the conclusion that there is little economically significant impact of being near a transportation network, which would support the Fogelian view. However, the relationship in the early 1990s shows how this is not the case. The question then arises, as to what happened in the two decades that weakened this relationship.

The period of study was one of rapid economic growth and development after reforms that liberalized the market structure, cut down on the license-permit bureaucracy and integrated various industries with world markets. It was also a period of upgrading the existing transportation network by strengthening the highway system. While the first set of regions were to benefit from being directly connected to the cities by being on the least-cost path of connectivity, over time other regions would establish indirect connections via these already connected regions. This would then lead to a protruding network structure that would link regions and spread development by lowering the costs of trade and exchange. This explanations can be ensconced in a growth-model framework by formalizing and estimating the extent of the spatial spillovers. The results in the paper indicate that a substantial amount of the high-rates of $\beta-$convergence can be explained by spatial spillovers in economic activity across neighboring regions.

As I show, ignoring these spillovers would have produced estimates of the impacts of these routes that are only 27% the size of the true overall effect – a gross underestimate. Furthermore, the implications for policy in the light of such spillovers can be crucial. While the initial transit networks did a lot to encourage economic activity in connected regions, future investments in upgrading these highways did little to help these regions indicating that investments in these highways had reached a portion of diminishing returns. However, the initial investments in the highways not only helped develop connected regions, but also led to spillovers in activity to neighboring regions. Together, these results indicate that, at the margin, policy-makers should try to connect more regions rather than upgrade routes on already connected regions.

Last, the existence of large spillovers can explain why past research on roads have found little impacts. An empirical strategy that compares regions along a route to neighboring regions will provide underestimates of the true impacts because economic activity may have spread to these neighboring regions by then. The existence of the spillovers indicate that the overall impacts of routes can be larger than previously thought, since roads can affect development not only on regions along the route, but regions farther away as well. In order to capture this spread of activity, therefore, it is important to study the impacts over time and pin down the entire pattern of spatial development, as I do in this paper.

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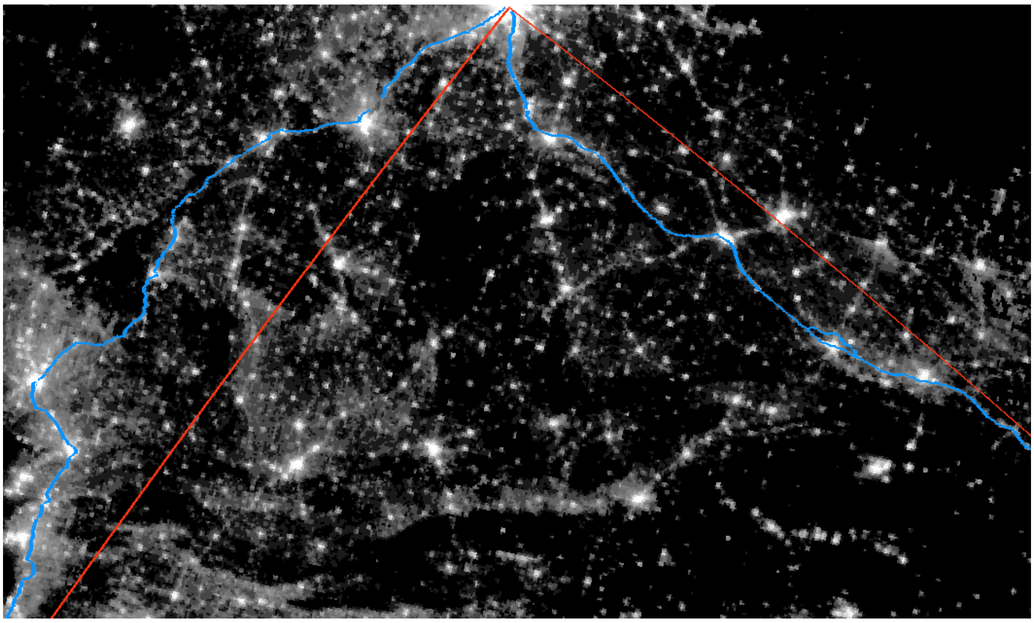
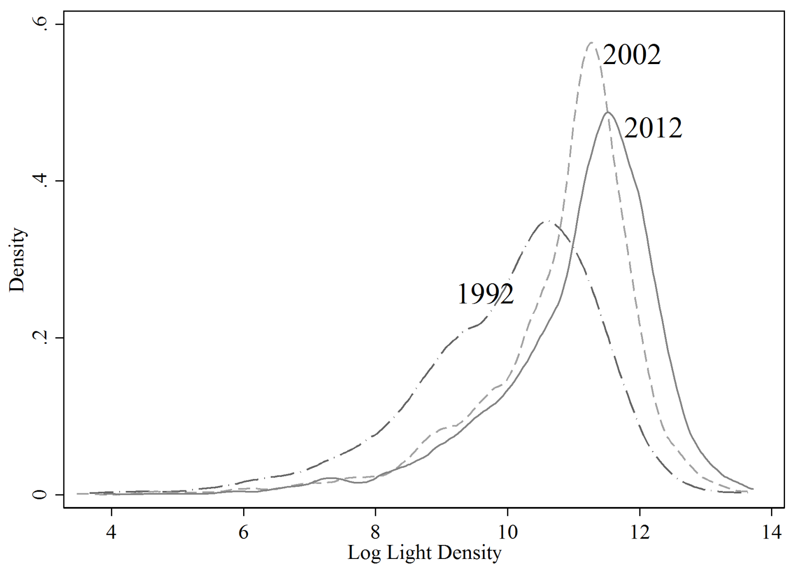
8 Tables and Figures



(a) Night-time lights, highways and straight-lines between Mumbai-Delhi and Delhi-Kolkata (The blue-line traces the actual route of the highway, and the red-line indicates the straight-line path between the major cities).



(b) Distribution of Log Light Density Over Time

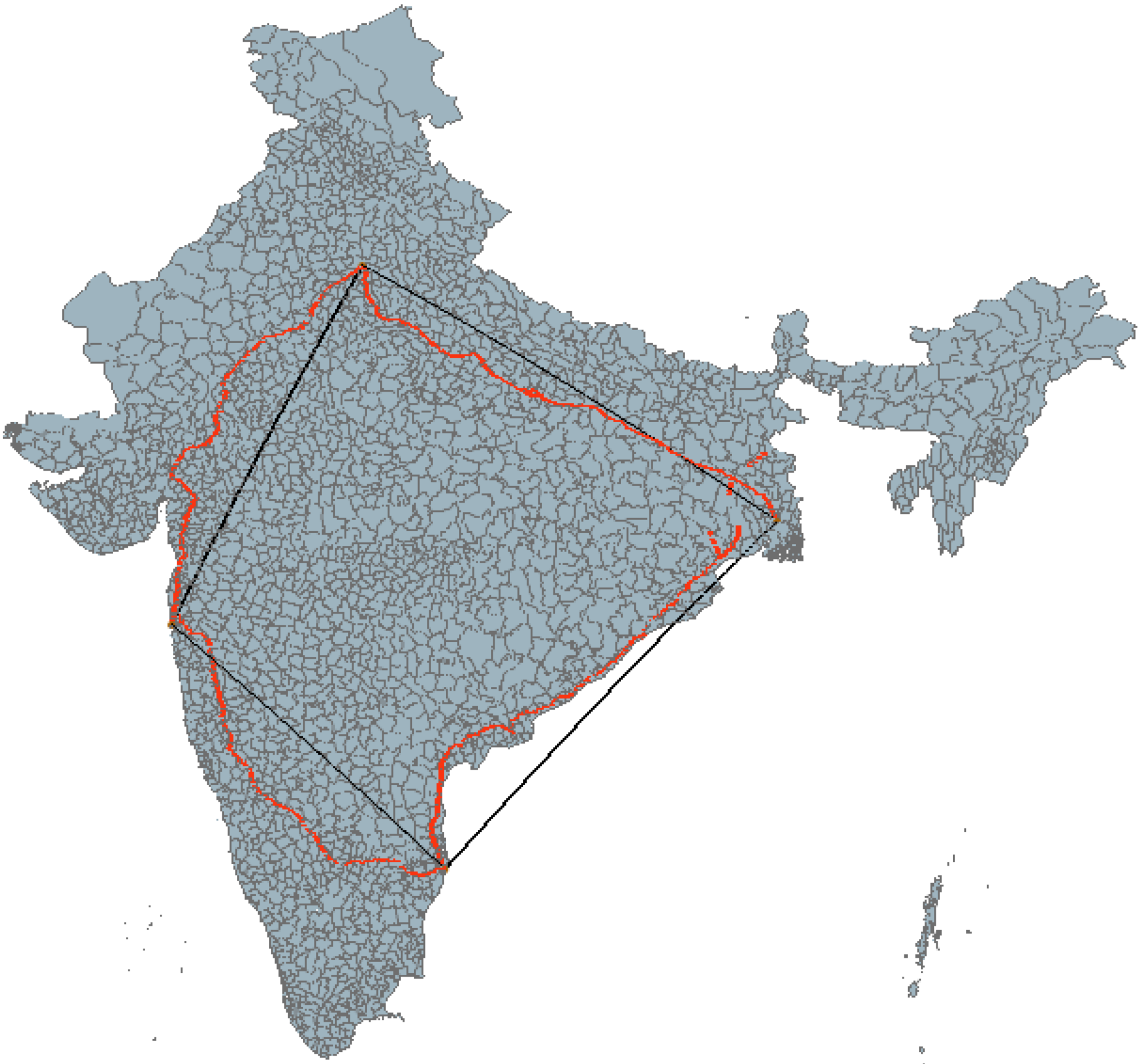
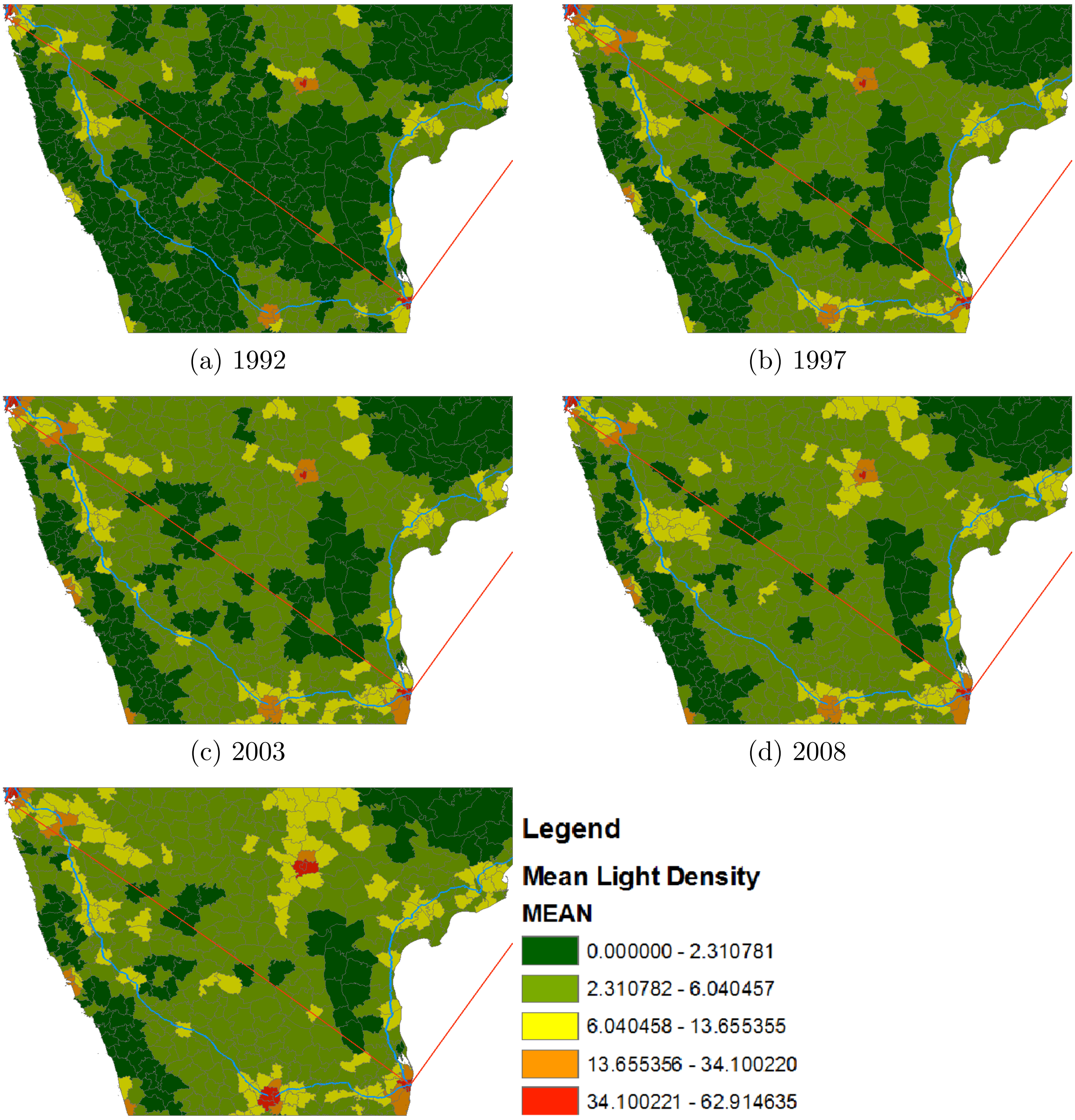


Figure 2: Golden Quadrilateral Highways and boundaries of the sub-districts used in the analysis.

Figure 3: Spread of Lights From the Mumbai-Chennai Highway



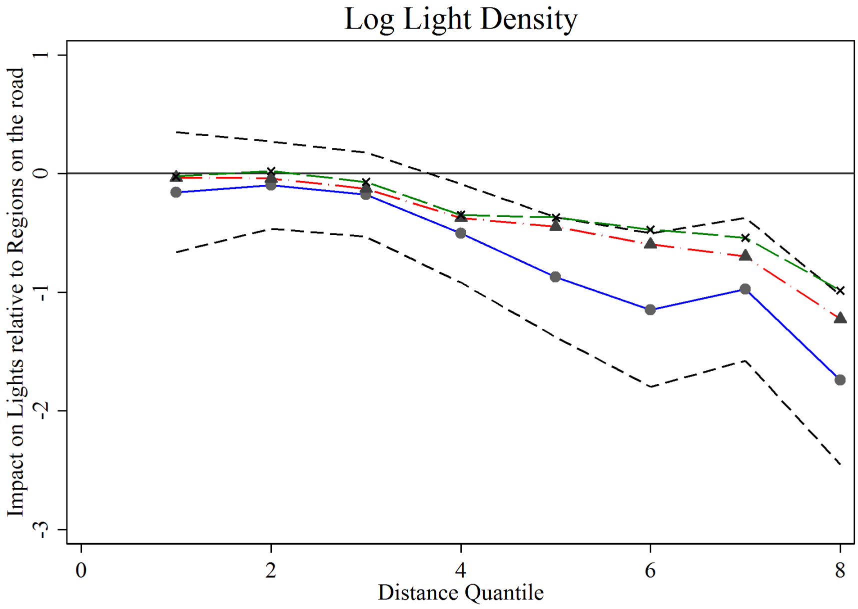
(a) 1992 (b) 1997

(c) 2003 (d) 2008

(e) 2012 (f)

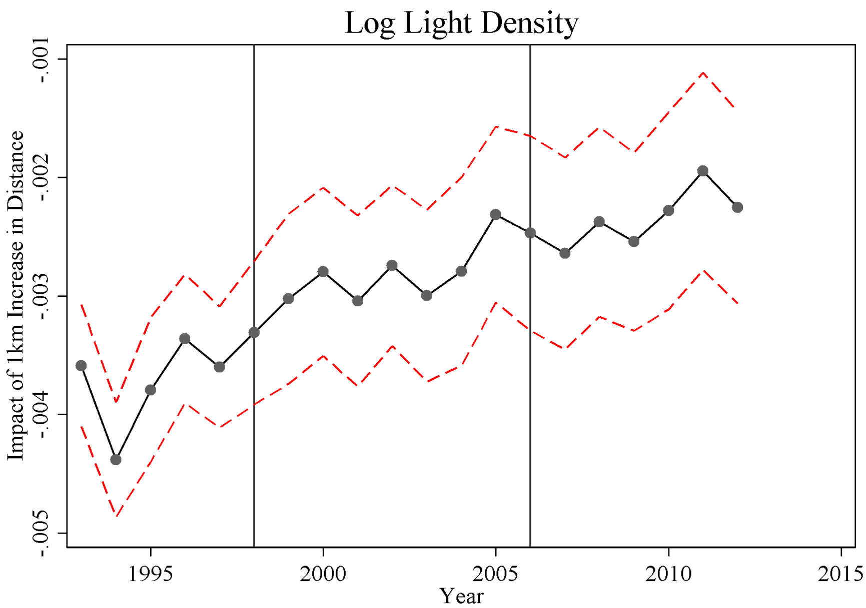
Displaying the spread of night-time light density every five years. The Blue Line indicates the actual path of the Highway, and the Red Line indicates the straight line connecting 2 major cities. The legend of light-densities is on a green to red spectrum, where green is relatively less light-density and red is a higher level of light-density

Figure 4: Changes in Light Density Over Distance Quintiles and Time



(a) Light Density (per sq miles)

The graphs show the impact of distance on night-time lights relative to sub-districts that have any portion of the sub-district touching the straight-lines. The blue lines are for the pre-upgrading period, the orange lines for the upgrading period and the green lines for the post-upgrading period. The standard error bands are for the pre-upgrading (blue) lines and clustered at the district level. The 'Distance' axis consists of 8 quantiles of equal size. The distance quantile cutoffs are roughly as follows: 0 to 40kms, 40 to 90 kms, 90 to 135 kms, 135 to 200kms, 200 to 260kms, 260 to 340 kms, 340 to 440 kms, and above 440kms. Different measures of night-time lights are presented in Figure A11. Robustness checks are presented in Figure A11



(b) Light-Density

Coefficients of change in impact relative to 1992. Standard errors calculated at the district level. Vertical lines represent the phases of upgrading - 1999 is when the highways started being upgraded. There were delays till 2001 when most work started, and 2006 is when most work was completed. To interpret the graph: the mean impact of a 1km increase in distance from the highway was a 0.00406 fall in light-density, and this impact has been dissipating over time. By 2012 the impact of a 1km increase in distance from the highway had become about -0.00201. Different measures of night-time lights are presented in Figure A10. Robustness checks are presented in Figure A12.

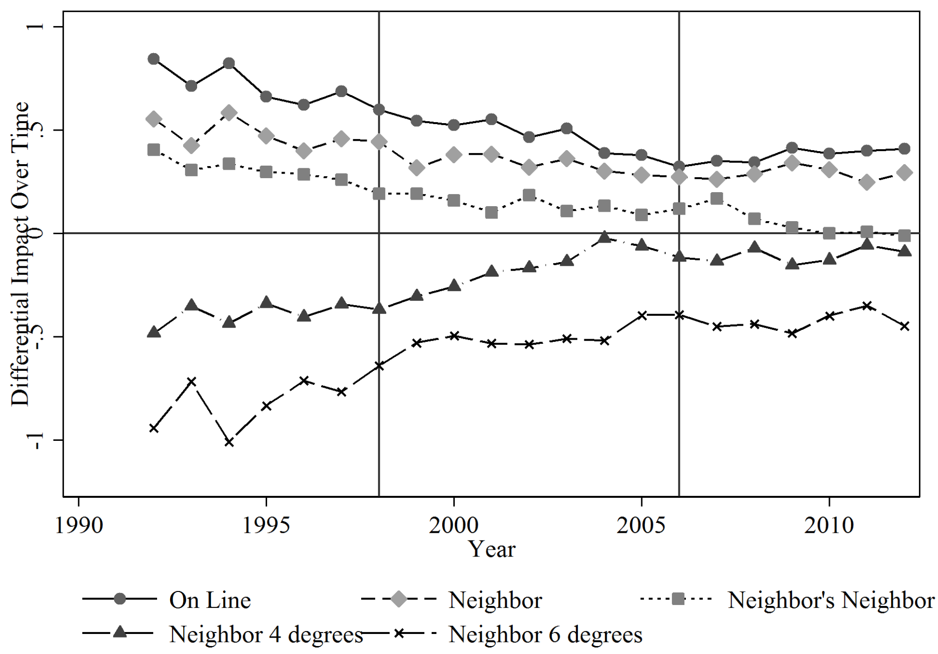


Figure 5: Relative light density for regions on the line, and their neighbors

Relative light density calculated as Log(light density) for that region relative to all other regions. “On Line” represents regions on the straight-line path between two major cities. “Neighbor” represents sub-districts that are neighbors of “On Line” sub-districts. “Neighbor’s Neighbor” represents neighbors of neighbors of “On Line” regions, and so on. “Neighbor 6 degrees” represents regions that are removed from “On Line” regions by more six-degrees of separation.

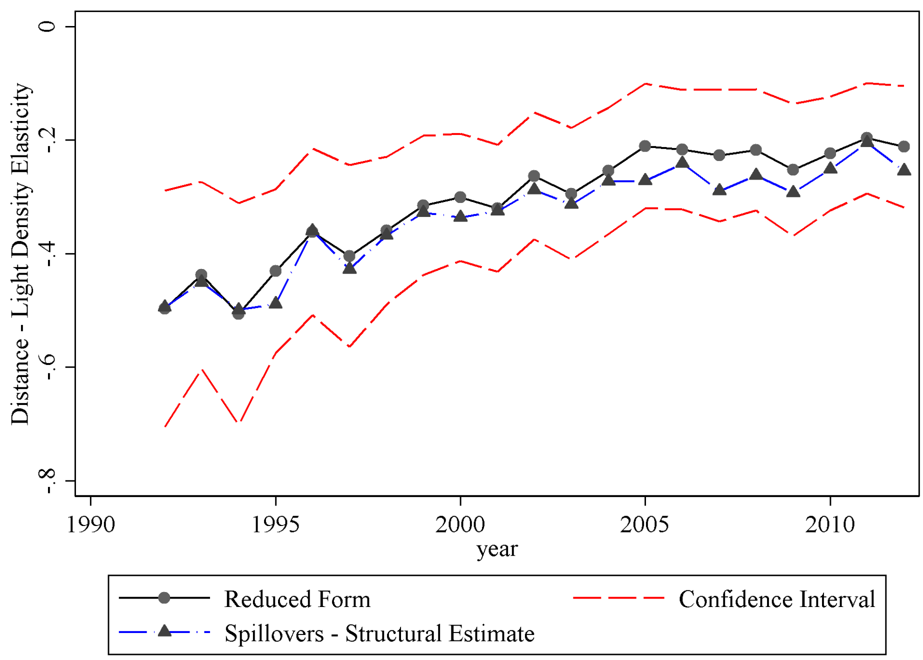


Figure 6: Spillovers & The Elasticity of Light Density with Respect to Distance

Elasticity of Light Density with respect to Distance to straight-line paths connecting historical major cities. The ‘Reduced Form’ line and corresponding confidence intervals plot the coefficient from the regression $Log\ LightDensity_{it} = \alpha_t Log\ Distance_{it} + \beta X + \epsilon_{it}$. The ‘Spillovers - Structural Estimate’ line plots the corresponding model-based elasticity as discussed in Section 6.4. As can be seen, the model fit is good as the structural estimates closely correspond to the reduced form estimates throughout this period.

Table 1: Predicting Distance to Routes with Distance to Straight-Lines

	Distance to GQ Highway		Distance to Railroad	
	Coefficient SE	First Stage F Stat	Coefficient SE	First Stage F Stat
Distance to Line	**0.81**		**0.055**	
SE clusters:				
Sub-district	(0.00983)	6796	(0.0215)	6.570
District	(0.0205)	1569	(0.0238)	5.348
State	(0.0372)	474.7	(0.0334)	2.707
R-squared	0.791	0.738	0.071	0.0516
Observations	2253	2253	2253	2253
Controls	Y	Y	Y	Y

Level of observation - sub-district

Dependent variable ‘Distance to GQ Highway’ is the nearest geo-distance between the the sub-district and the closest Golden Quadrilateral highway

Dependent variable ‘Distance to Railroad’ is the nearest geo-distance between the sub-district and the closest railway line

Independent variable ‘Distance to Line’ is the nearest geo-distance between the sub-district and closest straight-line connecting nodal cities

Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table 2: Relationship Between Night-Time Light Density and Distance to Transit Networks

	Log Light Density		
Year: 1992	**OLS**	**Reduced Form**	**IV 2SLS**
Distance (100km)	**-0.391**	**-0.406**	**-0.501**
SE Cluster:			
Sub-district	(0.0492)	(0.0479)	(0.0593)
District	(0.0784)	(0.0749)	(0.0933)
State	(0.177)	(0.159)	(0.194)
R-squared	0.144	0.152	0.141
Year: 2002	**OLS**	**Reduced Form**	**IV 2SLS**
Distance (100km)	**-0.224**	**-0.233**	**-0.287**
SE Cluster:			
Sub-district	(0.0332)	(0.0326)	(0.0404)
District	(0.0476)	(0.0442)	(0.0551)
State	(0.102)	(0.0884)	(0.109)
R-squared	0.188	0.193	0.185
Year: 2012	**OLS**	**Reduced Form**	**IV 2SLS**
Distance (100km)	**-0.193**	**-0.188**	**-0.232**
SE Cluster:			
Sub-district	(0.0316)	(0.0316)	(0.0391)
District	(0.0457)	(0.0432)	(0.0535)
State	(0.0849)	(0.0782)	(0.0965)
R-squared	0.156	0.157	0.155
Controls	Y	Y	Y
Observations	2,253	2,253	2,253

Level of observation - sub-district
Independent variable 'Distance' in OLS specification is 'Distance to GQ Highway' – the nearest geo-distance between the the sub-district and the closest Golden Quadrilateral highway
Independent variable 'Distance' in Reduced Form specification is 'Distance to Line' – the nearest geo-distance between the sub-district and closest straight-line connecting nodal cities
First stage of IV 2SLS specification is shown in Table 1 – Distance to GQ Highway is instrumented with Distance to nearest straight-line connecting nodal cities
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.
Dependent variable is Log(0.01+lights/area)

Table 3: Reduced Form and 2SLS: Elasticity of Lights, Distance and GDP

Reduced Form	Log Light Density					
Year	**1992**	**1996**	**2000**	**2004**	**2008**	**2012**
Log(Distance)	**-0.497**	**-0.362**	**-0.300**	**-0.254**	**-0.217**	**-0.212**
SE clusters:						
Sub-district	(0.0591)	(0.0462)	(0.0379)	(0.0365)	(0.0365)	(0.0364)
District	(0.106)	(0.0747)	(0.0571)	(0.0567)	(0.0543)	(0.0545)
State	(0.226)	(0.151)	(0.116)	(0.109)	(0.0944)	(0.0921)
R-Squared	0.135	0.160	0.170	0.196	0.154	0.147
GDP-distance elasticity	**0.1491**	**0.1086**	**0.09**	**0.0762**	**0.0651**	**0.0636**
Bootstrapped SE	(0.0164)	(0.0126)	(0.0110)	(0.0106)	(0.0119)	(0.0105)
IV - 2SLS	**Log Light Density**					
Year	**1992**	**1996**	**2000**	**2004**	**2008**	**2012**
Log(Distance)	**-0.735**	**-0.534**	**-0.444**	**-0.375**	**-0.321**	**-0.313**
SE clusters:						
Sub-district	(0.0852)	(0.0670)	(0.0546)	(0.0519)	(0.0524)	(0.0523)
District	(0.155)	(0.109)	(0.0819)	(0.0795)	(0.0772)	(0.0776)
State	(0.338)	(0.226)	(0.175)	(0.162)	(0.141)	(0.137)
R-Squared	0.124	0.148	0.164	0.202	0.159	0.155
GDP-distance elasticity	**0.2205**	**0.1602**	**0.1332**	**0.1125**	**0.0963**	**0.0939**
Bootstrapped SE	(0.0237)	(0.0207)	(0.0174)	(0.0167)	(0.0163)	(0.0140)
Observations	2,253	2,253	2,253	2,253	2,253	2,253
Controls	Y	Y	Y	Y	Y	Y

*Estimates of GDP-distance elasticity rely on elasticity of GDP-lights being 0.3 for low-middle income countries. Therefore to find elasticity of GDP-distance, multiply the coefficient with 0.3.
Level of observation - sub-district.
Independent variable 'Log (0.01+Distance to Line)' is the nearest geo-distance between the sub-district and the closest straight-line connecting Mumbai and Kolkata - two historical cities that have not had direct transit networks connecting them.
Dependent variables is Log(0.01 + Light density). 'Lights per area' normalizes the sum by the surface area of the district.
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table 4: The impact of distance changing over time

	Sum of Lights	Mean Lights	Light Density	P(Majority Lights>0)
Distance to Line	-3.257	-1.796	-3.389	-0.275
SE Level of Clusters:				
Sub-district	(0.357)	(0.184)	(0.386)	(0.0497)
District	(0.539)	(0.302)	(0.561)	(0.0893)
State	(1.088)	(0.643)	(1.187)	(0.155)
Distance*Upgrading Period	0.867	0.350	0.955	-0.0117
SE Level of Clusters:				
Sub-district	(0.136)	(0.0521)	(0.162)	(0.0259)
District	(0.161)	(0.0872)	(0.202)	(0.0445)
State	(0.351)	(0.232)	(0.397)	(0.117)
Distance*Post Period	1.232	0.526	1.388	0.0938
SE Level of Clusters:				
Sub-district	(0.173)	(0.0733)	(0.205)	(0.0306)
District	(0.206)	(0.120)	(0.247)	(0.0512)
State	(0.437)	(0.267)	(0.487)	(0.127)
R-Squared	0.144	0.285	0.203	0.208
Year Fixed Effects	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	47,313	47,313	47,313	47,313

Level of observation - sub-district. Distances in 1000 kms.
Independent variable 'Distance to Line' is the nearest predicted geo-distance between the sub-district and the closest straight-line connecting nodal cities
Dependent variables 'Sum of Lights', 'Mean Lights' and 'Lights per area' are of the form Log(0.01 + Lights). 'Sum of Lights' is the sum of pixels in a sub-district. 'Mean Lights' is the mean light intensity for pixels in a sub-district. 'Lights per area' normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the the majority of recorded lights was greater than 0 in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude, and year fixed effects. Results are robust to excluding controls.
Pre-upgrading period is 1992 to 1999, upgrading period is 1999 to 2006, and post-upgrading period is 2007 onwards.

Table 5: Elasticity between Population and Distance to Line

	Log (Population)					
Year	**2002**	**2004**	**2006**	**2008**	**2010**	**2012**
Log(Distance)	**-0.226**	**-0.182**	**-0.178**	**-0.179**	**-0.176**	**-0.191**
SE clusters:						
Sub-district	(0.0221)	(0.0293)	(0.0290)	(0.0290)	(0.0305)	(0.0305)
District	(0.0404)	(0.0560)	(0.0543)	(0.0545)	(0.0562)	(0.0559)
State	(0.0838)	(0.0991)	(0.0968)	(0.0969)	(0.0977)	(0.0970)
R-Squared	0.091	0.056	0.053	0.053	0.044	0.046
Observations	2,246	2,246	2,246	2,246	2,246	2,246
Controls	Y	Y	Y	Y	Y	Y

Population Data from LandScan, US Department of Energy
Independent variable 'Log (0.01+Distance to Line)' is the nearest geo-distance between the sub-district and the closest straight-line connecting Mumbai and Kolkata - two historical cities that have not had direct transit networks connecting them.
Dependent variables is Log(Population Density)
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table 6: Elasticity For Non-GQ Route: Mumbai to Kolkata

	Log (Light Density)					
Year	**1992**	**1996**	**2000**	**2004**	**2008**	**2012**
Log(Distance)	**-0.248**	**-0.147**	**-0.0735**	**-0.0822**	**-0.0273**	**-0.0520**
SE clusters:						
Sub-district	(0.0463)	(0.0351)	(0.0307)	(0.0300)	(0.0293)	(0.0294)
District	(0.0805)	(0.0520)	(0.0436)	(0.0425)	(0.0405)	(0.0404)
State	(0.179)	(0.118)	(0.0964)	(0.0845)	(0.0780)	(0.0743)
Observations	2,253	2,253	2,253	2,253	2,253	2,253
Controls	Y	Y	Y	Y	Y	Y
GDP-distance elasticity	0.0744	0.0441	0.02205	0.02466	0.00819	0.0156

*Estimates of GDP-distance elasticity rely on elasticity of GDP-lights being 0.3 for low-middle income countries. Therefore to find elasticity of GDP-distance, multiply the coefficient with 0.3.
Level of observation - sub-district.
Independent variable 'Log (0.01+Distance to Line)' is the nearest geo-distance between the sub-district and the closest straight-line connecting Mumbai and Kolkata - two historical cities that have not had direct transit networks connecting them.
Dependent variables is Log(0.01 + Light density). 'Lights per area' normalizes the sum by the surface area of the district.
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table 7: β-convergence and the Solow model

	$Log\frac{Lights(t)}{Lights(t-1)}$	$Log\frac{Lights(t=T)}{Lights(t=0)}$	Growth rate (Lights)
Log Lights (t-1)	-0.108		
	(0.0143)		
Log Lights (t=0)		-0.551	-0.0275
		(0.00998)	(0.00155)
R-squared	0.071	0.583	0.007
Controls	N	Y	Y
		Estimated Rate of Convergence	
β		**0.04**	**0.0392**
Bootstrapped SE		(0.00421)	(0.0128)

Standard errors clustered at the district level (587 districts)
Column 1 tests if unconditional convergence holds in this case using the specification discussed in Sala-i Martin (1996) and Barro and Sala-i Martin (2004)
Column 2 estimates the rate of β-convergence using the methodology discussed in Mankiw et al. (1992)
Column 3 estimates the rate of β-convergence using the methodology discussed in Evans (1997); Higgins et al. (2006)

Table 8: 2001 and 2011 Census: population, workers, and literacy

Log Population (2011 Census)	Rural	Total	Female	Male	SC	ST
Log(Distance)	-0.239	-0.218	-0.216	-0.220	-0.226	0.285
	(0.0394)	(0.0402)	(0.0401)	(0.0403)	(0.0474)	(0.0737)
Constant	16.85	17.86	17.16	17.17	13.91	7.284
	(0.802)	(0.798)	(0.799)	(0.797)	(0.966)	(1.153)
Observations	5,259	5,290	5,290	5,290	5,032	5,149
R-squared	0.211	0.205	0.203	0.207	0.064	0.025

Log Population (2001 Census)	Rural	Total	Female	Male	SC	ST
Log(Distance)	-0.213	-0.201	-0.200	-0.203	-0.351	0.300
	(0.0390)	(0.0397)	(0.0398)	(0.0397)	(0.0619)	(0.0763)
Constant	16.65	17.56	16.88	16.86	17.76	6.358
	(0.800)	(0.799)	(0.802)	(0.797)	(1.433)	(1.232)
Observations	5,269	5,293	5,293	5,293	5,112	5,050
R-squared	0.195	0.197	0.196	0.198	0.134	0.027

Census Year	2001 Log(cultivators) per capita	2011 Log(cultivators) per capita	2001 Log(Ag Laborers) per capita	2001 Log(workers in HH ind. per capita)	2001 Literacy Rate	2001 Gender Gap in literacy
Log(Distance)	0.0612	0.0868	-0.149	-0.0698	-0.111	-1.478
	(0.0227)	(0.0222)	(0.0336)	(0.0228)	(0.700)	(0.283)
Constant	3.326	2.323	1.207*	-3.391	125.3	18.93
	(0.455)	(0.544)	(0.632)	(0.360)	(8.507)	(4.073)
Observations	5,264	5,286	5,278	5,284	4,809	4,809
R-squared	0.073	0.035	0.268	0.081	0.090	0.119

Level of observation - Census Teshils (also called Taluks, Mandals and Wards depending on the region)
Standard errors calculated at the district level (587 districts)
SC are known as Scheduled Castes, and STs are Scheduled Tribes - which the two most economically and socially disadvantaged sections.
Gender Gap is defined as the male-literacy rate minus the female-literacy rate.

Table 9: Neighbors closer to the road vs. farther away from the road

	Contemporaneous effect	Lagged effect	Changes*
Log(light density) of neighbors closer to road	0.490 (0.0302)		
Lagged		0.370 (0.0269)	
Changes			0.332 (0.0427)
Log(light density) of neighbors further from road	0.351 (0.0356)		
Lagged		0.237 (0.0333)	
Changes			0.265 (0.0287)
Constant	1.648 (0.304)	4.138 (0.387)	0.0280 (0.00290)
Observations	45,045	42,900	42,900
R-squared	0.341	0.194	0.106
Fixed Effect Units	2,145	2,145	2,145

Fixed effects regressions - Level of observation - Sub-district-year
Standard errors calculated at the district level (587 districts)
This table tests whether neighbors closer to the highway have larger impacts than regions away from the highway.
* The 'Changes' version of the equation estimates $\Delta Log(lights)_{t,k} = \beta \Delta Log(lights)_{t,k-1} + \gamma \Delta Log(lights)_{t,k+1}$

Table 10: Spillovers from Neighbors and the effect of distance

Panel A **Log(Light density)**	**1992**	**1997**	**2003**	**2007**	**2012**
Log(light density) of neighbors	**0.868**	**0.827**	**0.773**	**0.843**	**0.802**
closer to road χ	(0.0491)	(0.0656)	(0.0637)	(0.0560)	(0.0762)
Log(distance) μ_t	**-0.104**	**-0.101**	**-0.0853**	**-0.0652**	**-0.064**
	(0.0376)	(0.0312)	(0.0254)	(0.0235)	(0.0225)
Observations	2,219	2,219	2,219	2,219	2,219
Controls	Y	Y	Y	Y	Y
R-squared	0.493	0.470	0.462	0.502	0.440
Distance-spillover parameter α_t	**-0.495**	**-0.429**	**-0.314**	**-0.290**	**-0.254**
Bootstrapped SE	(0.166)	(0.156)	(0.0999)	(0.117)	(0.112)

Panel B **Log(Light density)**	**1992**	**1997**	**2003**	**2007**	**2012**
Log(distance) α_t	**-0.497**	**-0.404**	**-0.294**	**-0.227**	**-0.212**
	(0.0591)	(0.0488)	(0.0388)	(0.0382)	(0.0364)
Observations	2,253	2,253	2,253	2,253	2,253
Controls	Y	Y	Y	Y	Y
R-squared	0.135	0.174	0.203	0.180	0.147

Panel C **Reduced Form**	**1992**	**1997**	**2003**	**2007**	**2012**
GDP-Distance Elasticity ignoring spillovers	-0.149	-0.121	-0.0789	-0.0681	-0.0635
Bootstrapped SE	(0.0164)	(0.0132)	(0.0123)	(0.0114)	(0.0105)
Overall Income Effects Incorporating Spillovers	**-0.149**	**-0.177**	**-0.2191**	**-0.2299**	**-0.2345**
IV 2SLS	**1992**	**1997**	**2003**	**2007**	**2012**
GDP-Distance Elasticity ignoring spillovers	-0.22	-0.179	-0.117	-0.101	-0.0938
Bootstrapped SE	(0.0237)	(0.0229)	(0.0158)	(0.0154)	(0.0140)
Overall Income Effects Incorporating Spillovers	**-0.22**	**-0.261**	**-0.323**	**-0.339**	**-0.3462**

Level of observation - Sub-district
Standard errors calculated at the district level (587 districts)
This table tests the model where light density y_{td} depends on light-density of the neighbors closer to the highway $y_{t,d-1}$ and distance to the highway D, in the following way: $Log\ y_{td} = \chi Log\ y_{t,d-1} + \mu_t Log\ D$. This relationship is estimated in Panel A. Furthermore, we can recursively solve, to show that $Log\ y_{td} = (\sum_{j=0}^{d} \chi^j)\mu_t Log\ D$, which is the parameter evaluated as the "Distance-spillover parameter" between the two panels for the average number of degrees-of-separation (i.e. $d = 6$). Panel B then tests if this parameter is equal to the parameter obtained by regressing $Log\ y_{td} = \alpha_t Log\ D$.
Panel C re-estimates the GDP-distance elasticities incorporating these spillovers and compares them to the elasticities where the spillovers were ignored.

A Additional Tables and Figures

Table A1: GDP and Distance to the Line

	Log (GDP per cap)					
Year	2000	2001	2002	2003	2004	2005
Distance (100 km)	-0.163	-0.158	-0.150	-0.144	-0.144	-0.140
	(0.0253)	(0.0255)	(0.0252)	(0.0255)	(0.0253)	(0.0253)
Observations	455	455	455	461	461	461
R-Squared	0.433	0.427	0.424	0.412	0.420	0.414
Controls	Y	Y	Y	Y	Y	Y

	Log (NDP per cap)					
Year	2000	2001	2002	2003	2004	2005
Distance (100 km)	-0.150	-0.144	-0.136	-0.132	-0.132	-0.130
	(0.0249)	(0.0252)	(0.0248)	(0.0253)	(0.0249)	(0.0250)
Observations	480	480	480	486	486	486
R-Squared	0.412	0.401	0.399	0.384	0.397	0.390
Controls	Y	Y	Y	Y	Y	Y

Regressions of Log(GDP – 1999 series) on Distance to the straight-line at the district level. Post 2005 the panel is no longer balanced and the number of districts drops.
District Domestic Product Sources: Department of Statistics and Programme Implementation, Government of West Bengal; Planning Commission; Directorate of Economics and Statistics Government of Uttar Pradesh; Department of Economics and Statistics Government of Tamil Nadu; Directorate of Economics and Statistics Government of Rajasthan; Department of Planning Government of Punjab; Planning and Coordination Government of Odisha; Directorate of Economics and Statistics Government of Maharashtra; Directorate of Economics and Statistics Government of Kerala; Planning Programme Monitoring and Statistics Department Government of Karnataka; Directorate of Economics and Statistics Government of Bihar; Directorate of Economics and Statistics Government of Assam; Andhra Pradesh State Portal
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A2: OLS relationship between night-time lights and distance to GQ highway: Different Measures of Lights

Year: 2012	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to GQ Highway	-2.016	-1.287	-1.929	-0.0536
SE clusters:				
Sub-district	(0.302)	(0.176)	(0.316)	(0.0614)
District	(0.469)	(0.289)	(0.457)	(0.107)
State	(0.858)	(0.577)	(0.849)	(0.190)
R-squared	0.084	0.220	0.156	0.201

Year: 1992	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to GQ Highway	-3.680	-1.654	-3.913	-0.217
Standard Errors Level of Clustering:				
Sub-district	(0.434)	(0.398)	(0.492)	(0.0582)
District	(0.701)	(0.731)	(0.784)	(0.0958)
State	(1.592)	(1.213)	(1.773)	(0.178)
R-squared	0.108	0.163	0.144	0.051
Controls	Y	Y	Y	Y
Observations	2,253	2,253	2,253	2,253

Level of observation - sub-district. Distances in 1000 kms.
Independent variable ‘Distance to GQ Highway’ is the nearest geo-distance between the sub-district and the closest Golden Quadrilateral highway
Dependent variables ‘Sum of Lights’, ‘Mean Lights’ and ’Lights per area’ are of the form Log(0.01 + Lights). ‘Sum of Lights’ is the sum of pixels in a sub-district. ‘Mean Lights’ is the mean light intensity for pixels in a sub-district. ‘Lights per area’ normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the sub-district has any visible lights emitted in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A3: Reduced-form relationship between Lights and straight-lines: Different Measures of Lights

Year: 2012	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Line	-1.919	-1.210	-1.876	-0.133
SE clusters:				
Sub-district	(0.305)	(0.171)	(0.316)	(0.0568)
District	(0.464)	(0.268)	(0.432)	(0.0942)
State	(0.778)	(0.517)	(0.782)	(0.136)
R-squared	0.085	0.220	0.157	0.202

Year: 1992	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Line	-3.805	-1.861	-4.060	-0.224
SE clusters:				
Sub-district	(0.420)	(0.216)	(0.479)	(0.0548)
District	(0.668)	(0.377)	(0.749)	(0.0923)
State	(1.402)	(0.794)	(1.588)	(0.167)
R-squared	0.117	0.173	0.152	0.052
Controls	Y	Y	Y	Y
Observations	2,253	2,253	2,253	2,253

Level of observation - sub-district. Distances in 1000 kms.
Independent variable 'Distance to Line' is the nearest geo-distance between the sub-district and the closest straight-line connecting nodal cities
Dependent variables 'Sum of Lights', 'Mean Lights' and 'Lights per area' are of the form Log(0.01 + Lights). 'Sum of Lights' is the sum of pixels in a sub-district. 'Mean Lights' is the mean light intensity for pixels in a sub-district. 'Lights per area' normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the sub-district has any visible lights emitted in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A4: Two-staged least squares relationship between lights and distance to GQ highways: Different Measures of Lights

Year: 2012	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to GQ Highway	-2.368	-1.494	-1.929	-0.164
SE clusters:				
Sub-district	(0.377)	(0.211)	(0.391)	(0.0699)
District	(0.572)	(0.331)	(0.535)	(0.117)
State	(0.951)	(0.638)	(0.965)	(0.167)
Pagan-Hall Het Test	72.25	129.2	68.56	183.6
p-value of Pagan-Hall	0	0	0	0
Year: 1992	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to GQ Highway	-4.697	-2.297	-5.011	-0.277
SE clusters:				
Sub-district	(0.521)	(0.266)	(0.593)	(0.0675)
District	(0.830)	(0.468)	(0.933)	(0.114)
State	(1.702)	(0.969)	(1.940)	(0.202)
Pagan-Hall Het Test	215.6	164.4	200.0	161.9
p-value of Pagan-Hall	0	0	0	0
Controls	Y	Y	Y	Y
Observations	2,253	2,253	2,253	2,253
Level of Clustering:	F-Stat	Prob>F	Hansen J	Partial R-sq
Sub-district	6796	0	0	0.738
District	1569	0	0	0.738
State	474.7	0	0	0.738

Level of observation - sub-district. Distances in 1000 kms.
Independent variable ‘Distance to GQ Highway’ is the nearest predicted geo-distance between the sub-district and the closest GQ highway, predicted by the distance to the closest straight-line connecting nodal cities
Dependent variables ‘Sum of Lights’, ‘Mean Lights’ and ’Lights per area’ are of the form Log(0.01 + Lights). ‘Sum of Lights’ is the sum of pixels in a sub-district. ‘Mean Lights’ is the mean light intensity for pixels in a sub-district. ‘Lights per area’ normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the sub-district has any visible lights emitted in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A5: Elasticity between Light-Density and State Domestic Product for 32 States

Per capita	GDP at	2005	prices					
Log(per cap GDP)	2005	2006	2007	2008	2009	2010	2011	2012
Log(light density)	0.19	0.198	0.19	0.191	0.183	0.198	0.192	0.186
	(0.0508)	(0.0503)	(0.0510)	(0.0545)	(0.0557)	(0.0617)	(0.0600)	(0.0589)
Constant	8.422	8.409	8.563	8.541	8.72	8.548	8.695	8.798
	(0.526)	(0.523)	(0.529)	(0.584)	(0.594)	(0.684)	(0.655)	(0.648)
Observations	32	32	32	32	32	32	32	32
R-squared	0.318	0.340	0.316	0.291	0.265	0.255	0.254	0.249
Per capita	NDP at	2005	prices					
Log(per cap NDP)	2005	2006	2007	2008	2009	2010	2011	2012
Log(light density)	0.191	0.199	0.191	0.192	0.186	0.202	0.196	0.191
	(0.0514)	(0.0508)	(0.0517)	(0.0549)	(0.0560)	(0.0626)	(0.0613)	(0.0606)
Constant	8.294	8.275	8.428	8.406	8.558	8.375	8.519	8.612
	(0.533)	(0.528)	(0.536)	(0.589)	(0.597)	(0.694)	(0.670)	(0.667)
Observations	32	32	32	32	32	32	32	32
R-squared	0.315	0.339	0.313	0.290	0.269	0.257	0.255	0.250

Regressions of Log(0.01+light density) on Log(per capita domestic product) at the state level.
State Domestic Product Sources: Reserve Bank of India
GDP indicates Gross Domestic Product of the State; and NDP is the Net Domestic Product

Table A6: Elasticity between Light Density and Per Capita District Domestic Product

Per capita NDP	at current	prices						
Log(per cap NDP)	2005	2006	2007	2008	2009	2010	2011	2012
Log(light density)	0.332	0.357	0.347	0.371	0.354	0.371	0.394	0.388
	(0.0236)	(0.0259)	(0.0264)	(0.0291)	(0.0249)	(0.0324)	(0.0296)	(0.0462)
Constant	6.213	5.988	6.16	5.82	6.103	5.762	5.661	5.75
	(0.241)	(0.268)	(0.274)	(0.312)	(0.264)	(0.361)	(0.323)	(0.518)
Observations	209	222	222	222	222	222	190	96
R-squared	0.488	0.463	0.439	0.426	0.479	0.373	0.485	0.428
Per capita NDP	at 2004-5	prices						
Log(per cap NDP)	2005	2006	2007	2008	2009	2010	2011	2012
Log(light density)	0.363	0.354	0.344	0.365	0.344	0.362	0.385	0.357
	(0.0230)	(0.0243)	(0.0261)	(0.0290)	(0.0244)	(0.0310)	(0.0287)	(0.0457)
Constant	5.915	6.071	6.302	6.113	6.516	6.238	6.223	6.591
	(0.238)	(0.252)	(0.271)	(0.312)	(0.260)	(0.347)	(0.315)	(0.511)
Observations	249	249	222	249	249	249	217	97
R-squared	0.502	0.463	0.440	0.391	0.446	0.356	0.456	0.391

Regressions of Log(0.01+light density) on Log(per capita domestic product) at the district level.
District Domestic Product Sources: Department of Statistics and Programme Implementation, Government of West Bengal; Planning Commission; Directorate of Economics and Statistics Government of Uttar Pradesh; Department of Economics and Statistics Government of Tamil Nadu; Directorate of Economics and Statistics Government of Rajasthan; Department of Planning Government of Punjab; Planning and Coordination Government of Odisha; Directorate of Economics and Statistics Government of Maharashtra; Directorate of Economics and Statistics Government of Kerala; Planning Programme Monitoring and Statistics Department Government of Karnataka; Directorate of Economics and Statistics Government of Bihar; Directorate of Economics and Statistics Government of Assam; Andhra Pradesh State Portal

Table A7: OLS relationship between lights and rail-lines: Different Measures of Lights

Year: 2012	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Railways	-9.321	-6.253	-8.82	-1.069
SE clusters:				
Sub-district	(5.341)	(2.885)	(4.656)	(0.400)
District	(5.536)	(2.954)	(4.816)	(0.403)
State	(7.584)	(3.997)	(6.552)	(0.530)
R-squared	0.096	0.232	0.164	0.207
Year: 1992	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Railways	-14.32	-7.884	-15.37	-0.862
SE clusters:				
Sub-district	(8.247)	(3.813)	(8.535)	(0.404)
District	(8.569)	(3.882)	(8.827)	(0.416)
State	(11.86)	(5.328)	(12.20)	(0.542)
R-squared	0.108	0.175	0.145	0.051
Controls	Y	Y	Y	Y
Observations	2,253	2,253	2,253	2,253

Level of observation - sub-district. Distances in 1000 kms.
Independent variable 'Distance to Railroad' is the nearest geo-distance between the sub-district and the closest Railway line
Dependent variables 'Sum of Lights', 'Mean Lights' and 'Lights per area' are of the form Log(0.01 + Lights). 'Sum of Lights' is the sum of pixels in a sub-district. 'Mean Lights' is the mean light intensity for pixels in a sub-district. 'Lights per area' normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the sub-district has any visible lights emitted in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A8: Two staged least squares relationship between lights and distance to railways: Different Measures of Lights

Year: 2012	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Railways	-34.86	-21.99	-34.09	-2.412
SE clusters:				
Sub-district	(14.51)	(8.781)	(14.32)	(1.271)
District	(15.63)	(9.903)	(15.91)	(1.856)
State	(22.23)	(14.34)	(22.31)	(2.669)
Pagan-Hall Het Test	24.15	18.87	23.54	52.75
p-value of Pagan-Hall	0.000203	0.00203	0.000266	0
Year: 1992	Sum of Lights	Mean Lights	Lights per area	P(Majority Lights>0)
Distance to Railways	-69.14	-33.82	-73.77	-4.076
SE clusters:				
Sub-district	(28.20)	(13.48)	(30.25)	(1.831)
District	(30.19)	(15.06)	(33.09)	(2.293)
State	(42.09)	(21.36)	(45.97)	(3.562)
Pagan-Hall Het Test	42.88	25.49	38.05	12.99
p-value of Pagan-Hall	0	0.000112	0	0.0235
Controls	Y	Y	Y	Y
Observations	2,253	2,253	2,253	2,253
Level of Clustering:	F-Stat	Prob > F	Hansen J	Partial R-sq
Sub-district	6.570	0.0104	0	0.0516
District	5.348	0.0211	0	0.0516
State	2.707	0.109	0	0.0516

Level of observation - sub-district. Distances in 1000 kms.
Independent variable ‘Distance to Railroad’ is the nearest predicted geo-distance between the sub-district and the closest rail-line, predicted by the distance to the closest straight-line connecting nodal cities
Dependent variables ‘Sum of Lights’, ‘Mean Lights’ and ’Lights per area’ are of the form Log(0.01 + Lights). ‘Sum of Lights’ is the sum of pixels in a sub-district. ‘Mean Lights’ is the mean light intensity for pixels in a sub-district. ‘Lights per area’ normalizes the sum by the surface area of the district. Dependent variable P(Majority Lights>0) is a 1/0 indicator variable for if the the majority of recorded lights was greater than 0 in that year
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

Table A9: Density of non-GQ Highways

	Reduced Form Results		
Log Road Density	**Other National Highways**	**Large State Highways**	**Smaller State Highways**
Log Distance	-0.126	-0.246	-0.308
SE Cluster:			
Sub-district	(0.0791)	(0.0608)	(0.0724)
District	(0.108)	(0.0699)	(0.0898)
State	(0.133)	(0.0904)	(0.116)
R-squared	0.010	0.010	0.010

Level of observation - sub-district. Independent variable Log(0.01+distance in kilometers to the straight line).
Dependent variable 'Log Road Density' is the Log(0.01 + sum of road length / area)
Controls include distance to nearest nodal city, coastline, latitude and longitude. Results are robust to excluding controls.

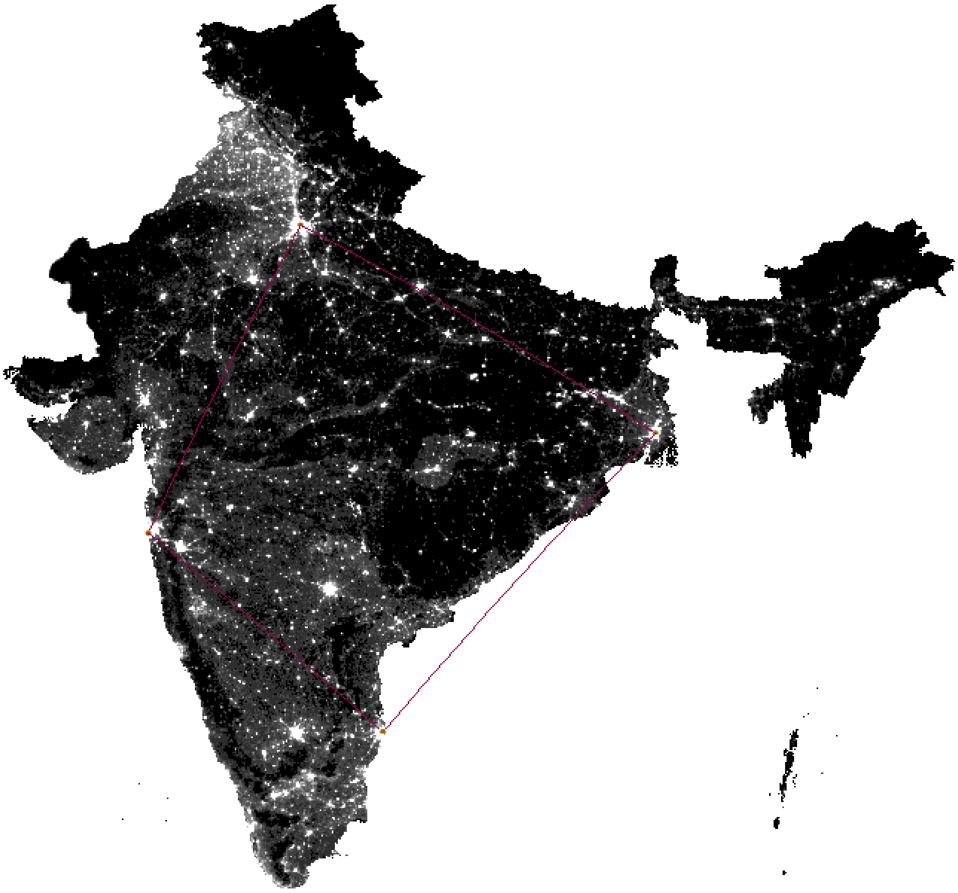


Figure A7: Night-time lights and straight-lines between four nodes

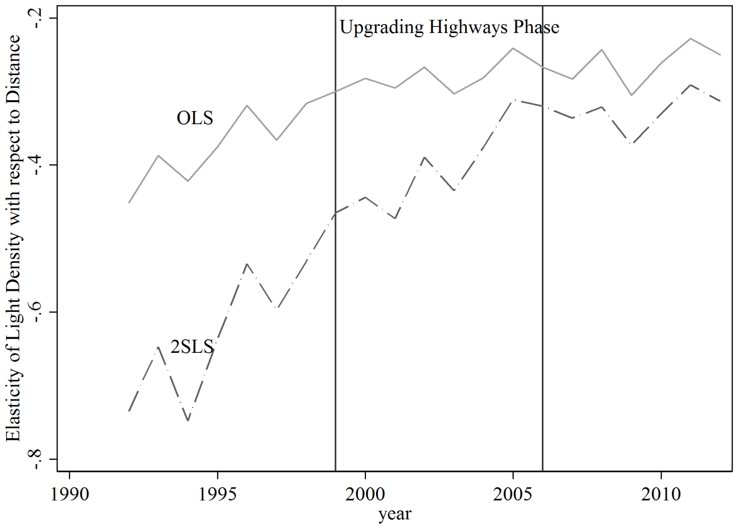
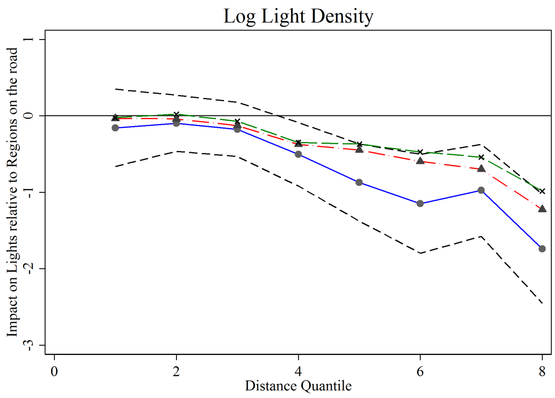


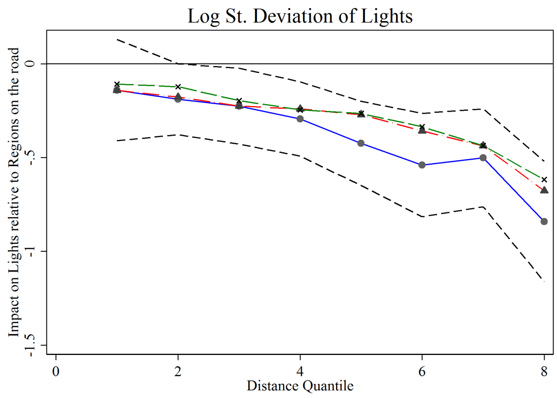
Figure A8: Change in Elasticities Over Time

Elasticities calculated by running a log-log relationship between lights and distance. Vertical lines represent the phases of upgrading - 1999 is when the highways started being upgraded. There were delays till 2001 when most work started, and 2006 is when most work was completed.

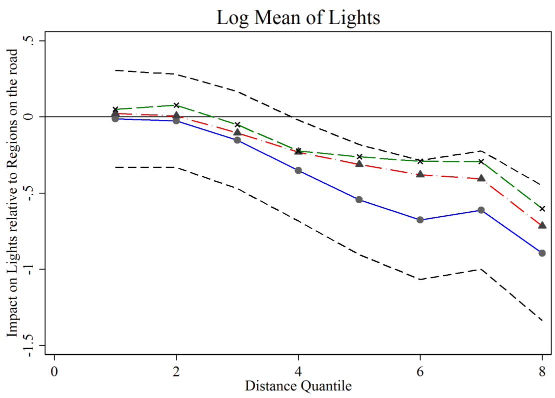
Figure A9: Impact of distance on lights: Different Measures of Light Density



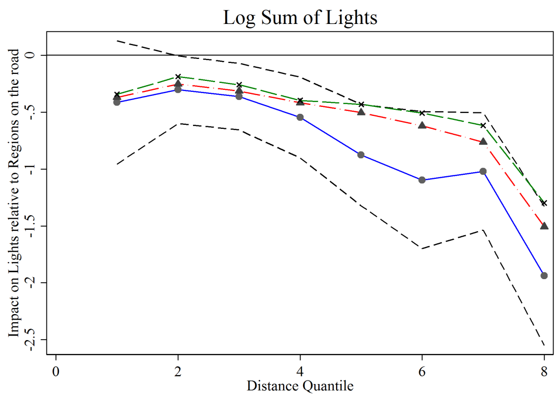
(a) Light Density (per sq miles)



(b) Standard Deviation of Lights



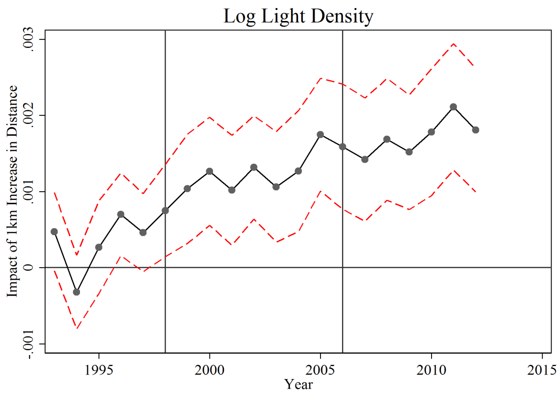
(c) Mean Lights



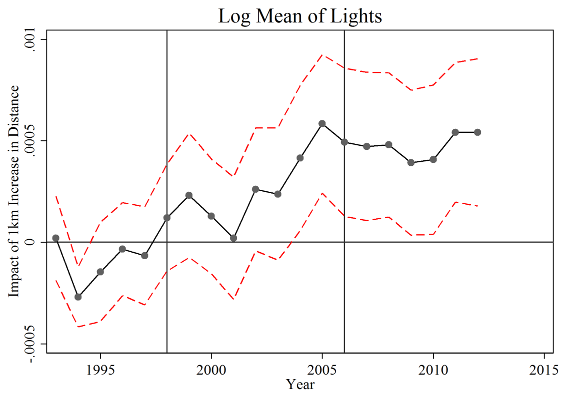
(d) Sum of lights

The graphs show the impact of distance on night-time lights relative to sub-districts that have any portion of the sub-district touching the straight-lines. The blue lines are for the pre-upgrading period, the orange lines for the upgrading period and the green lines for the post-upgrading period. The standard error bands are for the pre-upgrading (blue) lines and clustered at the district level. The 'Distance' axis consists of 8 quantiles of equal size. The distance quantile cutoffs are roughly as follows: 0 to 40kms, 40 to 90 kms, 90 to 135 kms, 135 to 200kms, 200 to 260kms, 260 to 340 kms, 340 to 440 kms, and above 440kms.

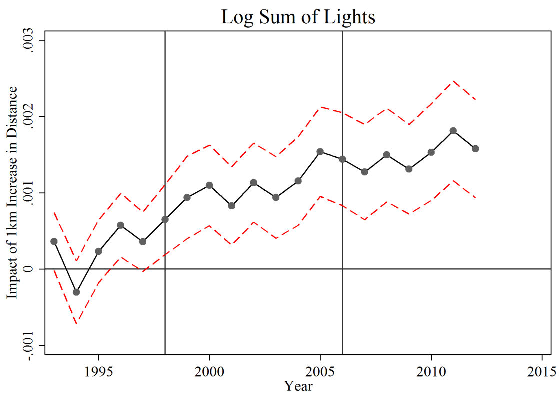
Figure A10: How the Impact of Distance on Light-Density changes over time (relative to 1992): Different Measures of Light Density



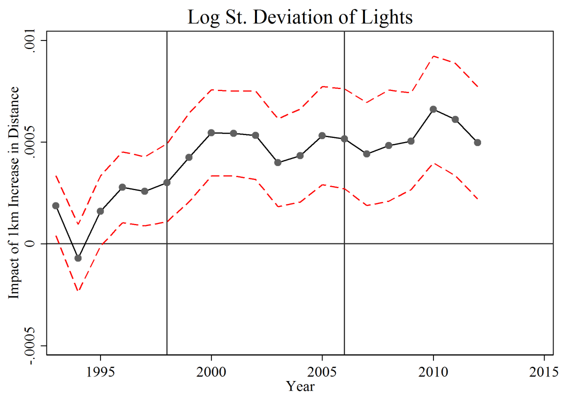
(a) Light-Density:1992 coefficient -0.00406



(b) Mean-lights. 1992 cofficient is -0.00186



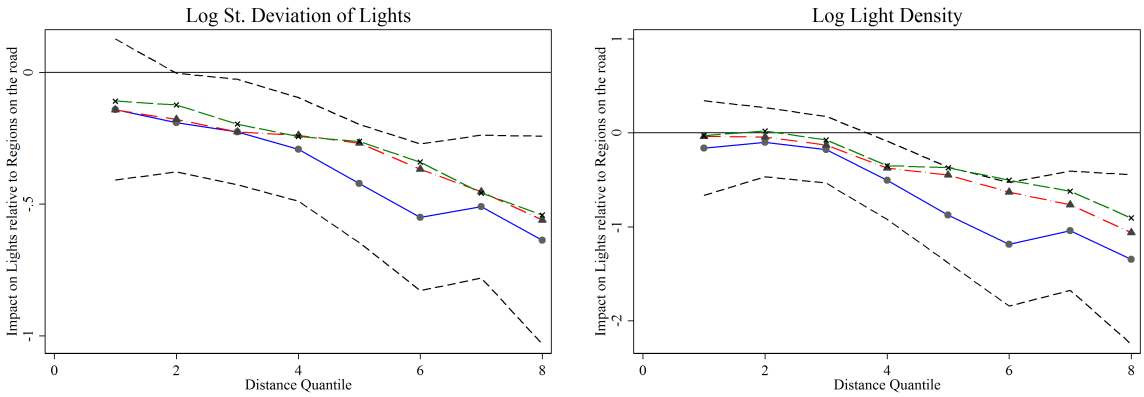
(c) Sum of lights: 1992 coefficient is -0.0038



(d) Standard Deviation of Lights -0.00174

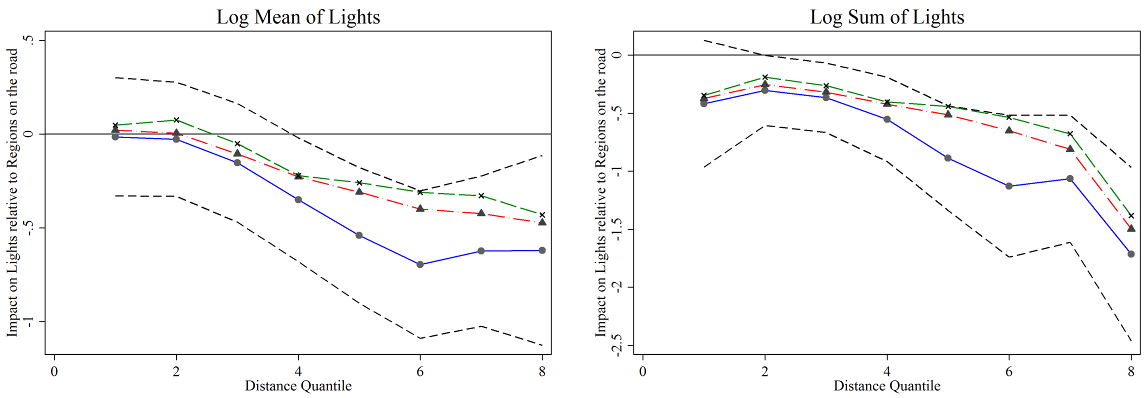
Coefficients of change in impact relative to 1992. Standard errors calculated at the district level. Vertical lines represent the phases of upgrading - 1999 is when the highways started being upgraded. There were delays till 2001 when most work started, and 2006 is when most work was completed. To interpret the graph: the mean impact of a 1km increase in distance from the highway was a 0.00406 fall in light-density, and this impact has been dissipating over time. By 2012 the impact of a 1km increase in distance from the highway had become -0.00406+0.00205, or about -0.00201.

Figure A11: Robustness Checks: Impact of distance on lights excluding outlying states



(a) Standard Deviation of Lights

(b) Light Density (per sq miles)

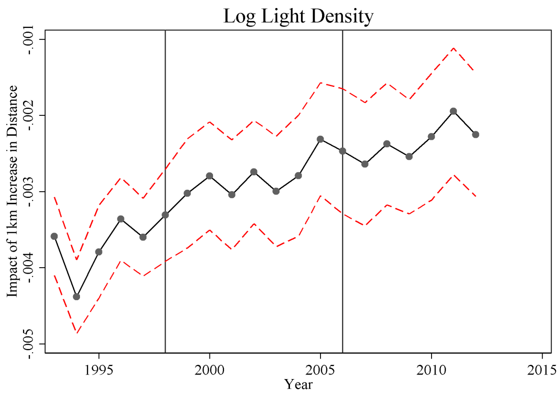


(c) Mean Lights

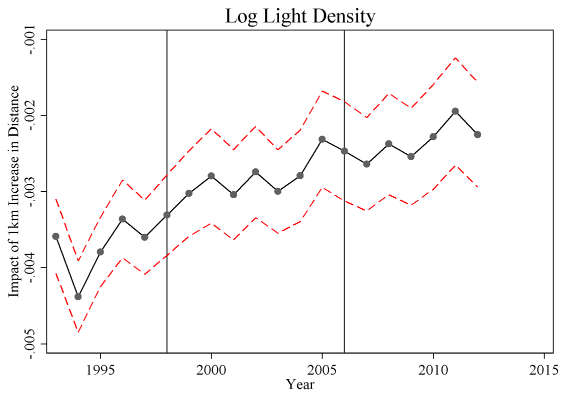
(d) Sum of lights

The excluded states in this robustness check include: Jammu and Kashmir, Manipur, Meghalaya, Tripura, Nagaland, Sikkim, Assam, Arunachal Pradesh, Mizoram, Andaman and Nicobar Islands and Lakshwadeep. The graphs show the impact of distance on night-time lights relative to sub-districts that have any portion of the sub-district touching the straight-lines. The blue lines are for the pre-upgrading period, the orange lines for the upgrading period and the green lines for the post-upgrading period. The standard error bands are for the pre-upgrading (blue) lines and clustered at the district level. The 'Distance' axis consists of 8 quantiles of equal size. The distance quantile cutoffs are roughly as follows: 0 to 40kms, 40 to 90 kms, 90 to 135 kms, 135 to 200kms, 200 to 260kms, 260 to 340 kms, 340 to 440 kms, and above 440kms.

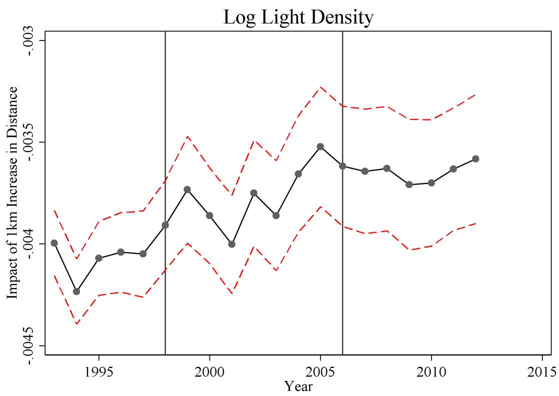
Figure A12: Robustness Checks: Different samples and specifications for: How the Impact of Distance on Light-Density changes over time



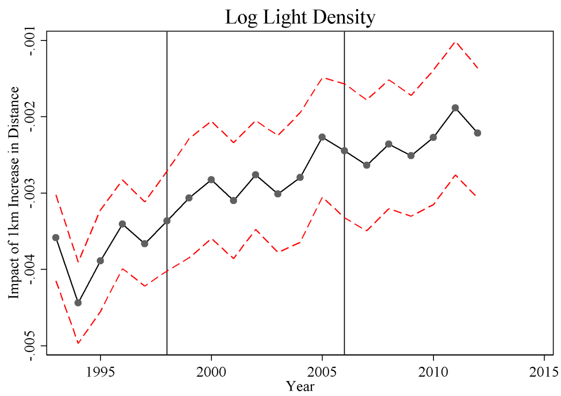
(a) District-level clusters



(b) Sub-district clusters



(c) Dropping 0s - Log(lights/area)



(d) Dropping extremely high light-density

Coefficients of change in impact relative to 1992. The impact of a 1km increase in distance in 1992 was a 0.00406 reduction in light density. Vertical lines represent the phases of upgrading - 1999 is when the highways started being upgraded. Standard errors calculated at the district level unless otherwise mentioned There were delays till 2001 when most work started, and 2006 is when most work was completed. The 'Dropping extremely high light-density' panel drops all sub-districts if they ever recorded a light pixel equal to the maximum possible value (63). This is 12% of the sample.

B Mobility and Convergence

One factor that may contribute to the dissipation of the effects of these routes may lie with the mobility of firms and people. However, such a model of mobility patterns would have to explain why capital or workers move *away* from the road over time. If the upgradation of highways actually allowed firms and workers to move away from the highway, then that may explain the spread in economic activity to regions further away.

B.1 Movement of Capital and Firms

The first is a location choice model for firms and capital. While the long-run positive impacts of the road suggest that firms locate to regions along these routes, somewhat more complex models are needed to explain why firms may move away over time. In such a model, upgrading the highway and therefore better connectivity on the highway system allows firms and households to locate further away from the highway. A firm or household enterprise wishes to be connected to the four nodal cities for purposes of trade and exchange. For locations that are not near the nodal cities, the cost of being connected to the city is the sum of the cost of being connected to the highway $c_1(d)$ and the cost of using the highway to get to the city c_2, where $c_1(d)$ is an increasing function of the distance between the region and the closest highway d.[22] Firms have returns to investment that is drawn from a distribution $R \sim F(.)$ and choose to locate in region d if $R \geq c_1(d) + c_2$. The fraction of firms that locate there are therefore $1 - F(c_1(d) + c_2)$. Since the cost functions are increasing in the distance, this would indicate that more firms will locate closer to the highways. Once the highway is upgraded, this reduces c_2, thereby allowing the same firm to locate at a distance d' further away from the highway. After the NHDP upgrades, firms and households can therefore move into regions that would earlier have been too costly for them to locate in. Note that in such a model, firms are no longer profit maximizing – lowering the credibility of such a model.

The strongest evidence against this model is the result shown in Ghani et al. (2015) who find that when the highways are upgraded, organized manufacturing firms actually move closer to the highway. Similarly, Redding and Turner (2015) discuss how it is likely that firms would move from 'untreated' to 'treated' regions when highways are built.

B.2 Movement of People

Another model is that of lowering costs of seasonal migration. Once the highways are upgraded, this allows people from near the highways to migrate to the city at lower costs. If the migration is permanent, there will be a fall in population and economic activity in the region close to

[22] c_2 can also be made to depend on the distance on the highway from the city, but is irrelevant for this analysis

the highway. In the Indian context, migration for work is low Munshi and Rosenzweig (2016), and Table 5 shows that at least long-run migration cannot drive the dynamic results. However, a lot of the migration in the Indian context is seasonal in nature, where people work in the cities during the agricultural slack season but on the farms in the peak season. For a city wage W_c that lies between the peak season w_p and slack season w_s wages, after taking into account the cost of migrating c_m, a laborer word work in the city during the agricultural slack season and return to his fields in the peak season. If a worker doesn't migrate in the slack season (he lives in a region where c_m is high), then he would engage in non-agricultural economic activity instead, but if he does migrate (c_m is low) then there is no need for non-agricultural enterprises to exist in these regions since in the slack season workers would easily migrate to the city. A lowering of migration costs by upgrading the highways would then facilitate seasonal migration and thereby reduce any non-agricultural enterprises from setting up in rural areas near the highways.