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Trade Liberalization and Local Development in India: Evidence from Nighttime Lights

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Abstract

We study the impact of the Indian trade liberalization of 1991 on development at the district level using satellite nighttime lights per capita as a proxy for development. We find that on average trade liberalization increased nighttime lights per capita but there was considerable heterogeneity in the effect. In particular, districts in states with flexible labor laws, districts with better road networks, proximity to the coast, or higher female labor force participation rate seem to have benefited more than other districts.

Keywords: trade liberalization, nighttime lights, per capita income, tariffs, labor laws
JEL codes: F13, F14, O11, O24

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I. Introduction

While the older empirical literature on trade focused on the impact of trade liberalization on country-level outcomes such as GDP, wages, inequality, unemployment, etc., a lot of recent work has started looking at the local effects of trade liberalization using more granular data.³ This is motivated by the fact that factors of production are highly immobile across space and sectors (at least in the short run) and hence globalization and technology shocks have heterogeneous effects across space within a country. This paper contributes to this emerging literature by studying the impact of a large episode of trade liberalization in India on district-level development where development is proxied by nighttime lights.

It is a standard practice to use per capita GDP as a measure of overall welfare or development in empirical analysis, however, district-level per capita income data are not available for all districts regularly in India. As a result, several recent papers have started using satellite nighttime lights as a proxy for district-level GDP in India⁴. The nighttime light data has the key advantage of availability at higher levels of spatial disaggregation. As a result, they have been widely accepted as a proxy for overall economic development at the national and particularly sub-national levels where data are either not available or of questionable quality.⁵

We use district-level tariff data before and after the episode of large trade liberalization in India which started in 1991. The sudden and unanticipated nature of this liberalization, which is crucial for identification, has been discussed extensively in the literature.⁶ The district-level tariffs are constructed by weighting industry tariffs by the initial period share of the district's workforce in that industry. Using nighttime lights per capita as a proxy for overall development at the district level in India, we find that the districts experiencing larger decreases in tariffs had larger increases in nighttime lights per capita. In terms of magnitude, the estimates from our benchmark instrumental variable specification suggest that a decline in tariffs of 6.9 percentage points (the average district-level tariffs declined by this amount) was associated with a 13% increase in

³ e.g. Chiquiar (2008), Topalova (2010), Kovak (2013), Autor et al. (2013)

⁴ e.g. Chanda and Kabiraj (2020), Jha and Talathi (2021)

⁵ e.g. Chen and Nordhaus (2011), Henderson et al. (2012), Donaldson and Storeygard (2016), Pinkovskiy and Sala-i-Martin (2016), Prakash, Rockmore, and Uppal (2019), Chanda and Kabiraj (2020)

⁶ e.g. Hasan et al. (2007), Topalova (2010)

nighttime lights per capita which translates into a 2.86% increase in GDP per capita.⁷ We also find heterogeneity in the effect of trade liberalization on development. In particular, districts in states with flexible labor laws benefited more from trade liberalization than districts in other states. Additionally, districts with better road infrastructure and proximity to the coast benefitted more. Somewhat surprisingly, districts with better rail networks didn't benefit more from trade liberalization. Finally, we also looked at the female labor force participation rate which is a strong correlate of development and found that districts with higher female labor participation rates benefited more from trade liberalization.

The remainder of our paper is structured as follows. In the next section, we provide a brief review of the related literature. Section III provides a discussion of our nighttime lights and tariffs data. Section IV provides the main empirical results and section V provides concluding remarks.

II. Related Literature

Our work is related to the growing literature studying the local effects of globalization such as Chiquiar (2008) for Mexico, Kovak (2013) for Brazil, and Autor et al. (2013) for the US. The study most closely related to our work is the influential paper by Topalova (2010) which finds that rural districts more exposed to trade liberalization experienced a slower decline in poverty and a lower increase in per capita consumption. Since per capita consumption data for urban areas are not available at the district level, the analysis for urban areas is conducted at the NSS regional level which is a higher level of aggregation and the results there are less clear cut. Compared to Topalova (2010), our proxy for development, nightlights per capita, does not distinguish between rural and urban areas within a district and finds a positive effect of trade liberalization on overall development. While the NSS data, on which Topalova (2010) relies, are based on a sample of 75000 rural and 45000 urban households spread over 466 districts (according to 1991 district boundaries) with considerable scope for sampling bias, our satellite data provide a comprehensive and uniform coverage of all districts.

⁷ Chanda and Kabiraj (2020) provide a range of 0.2 to 0.24 for the elasticity of state domestic product per capita with respect to nightlights per capita using state level data from India. Our estimate of a 2.55% increase in GDP per capita is based on taking the middle value of the range 0.2 to 0.24.

Another closely related study is Hasan et al. (2007) which studies the impact of trade liberalization on poverty in India using state-level data. Unlike Topalova (2010), they do not find evidence of a slower decline in poverty in states experiencing larger trade liberalization. Both Topalova (2010) and Hasan et al. (2007) find the gains from trade liberalization to be positively associated with labor market flexibility, a finding that we also confirm with our nightlights data. Hasan et al. (2007) also find that trade liberalization has a larger negative effect on poverty in states with a greater density of roads. This is broadly consistent with our finding of trade liberalization having a larger positive effect on nightlights per capita in districts with greater road length per capita. Neither of these papers studies how the length of railroads or the female labor force participation rates affect the impact of trade liberalization.

In a recent paper, Chor and Li (2021) study the impact of the US-China tariff war using high-frequency grid-level nighttime lights data. Using within-grid variation over time, similar to our identification strategy of within-district variation over time, they find that a 1 percentage point increase in exposure to the US tariffs was associated with a 0.59% reduction in nighttime lights.

Our paper is also related to the broader literature that has established a strong positive relationship between nighttime lights and GDP at both national and sub-national levels. Donaldson and Storeygard (2016) provide a survey of this literature. In the Indian context, Prakash, Rockmore, and Uppal (2019) use nightlights as a proxy for economic activity to show that electing criminally accused politicians reduces the growth of economic activities significantly. Chodorow-Reich et al. (2019) use it to show the adverse effect of the 2016 Indian demonetization episode on economic activity. Chanda and Kabiraj (2020) use district-level nightlights per capita data to show the convergence in development over the period 1996-2010. Jha and Talathi (2021) show the adverse effects of direct British rule (compared to districts under indirect rule) on development and growth since the early 1990s using district-level data on nightlights per capita.

III. Data

We conduct our analysis at the district level (1991 Census) within India. As per the 1991 Census of India, India was divided into 466 districts that constitute 32 states.⁸ We follow Topalova (2010)

⁸ As per the 1991 Census, India was divided into 25 States and 7 Union Territories. We refer to these 32 sub-national administrative units as *States* in our paper.

and focus our analysis on 394 districts spread across 17 major states of India.⁹ Since we obtain much of our data from Topalova (2010), who conducts her analysis as per the 1987-88 NSS districts, we match the districts in her analysis to the 1991 Census districts following the methodology of Castelló-Climent et al. (2018) and Jha and Talathi (2021).¹⁰ Summary statistics of the variables used in our analysis are presented in Table 1.

III.1 Nighttime lights Per Capita

The Earth Observation Group (EOG) of the Payne Institute for Public Policy at the Colorado School of Mines maintains images of lights generated from the earth's surface at nighttime that are captured by satellites of the National Oceanic and Atmospheric Administration (NOAA). These images are available at an annual frequency for years spanning 1992 – 2021. Of the many nighttime light data products available, for our analysis, we are mainly interested in nighttime light data from 1992 to 2001. The 'stable' nighttime lights product of the DMSP-OLS (Defense Meteorology Satellite Program – Operational Linescan System) data series is widely used in studies whose analysis spans 1992 – 2013.¹¹ For each year, the EOG makes available an annual composite image of lights generated from the earth's surface at nighttime. For the years 1994 and 1997 – 2007, there are two images available for each of these years – one captured by the newer satellite and the other captured by the older satellite. Each image housed by the EOG consists of billions of pixels with each pixel emitting varying intensities of nighttime lights. These pixels are scaled to a 30-arc-second grid between 65° south and 75° north latitudes. A digital number (DN) is used to measure the luminosity of nighttime lights emitted from each pixel. The DN in the 'stable' nighttime lights data product ranges from 0 to 63 with a DN of 0 implying almost no light emitted and 63 representing the highest possible intensity of nighttime lights that can be emitted from a pixel.

⁹ To remain consistent with the analysis in Topalova (2010) and to have the same controls, we focus our analysis across districts in the 17 major states. The 17 major states in our analysis include Andhra Pradesh, Assam, Bihar, Delhi, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

¹⁰ Following Jha and Talathi (2021) and Castelló-Climent et al. (2018), we assign the same data value to 1991 Census districts that were part of the same geographic boundary in 1987-88 (as per the 43rd round NSS data).

¹¹ Henderson et al. (2012), Pinkovskiy and Sala-i-Martin (2016), Prakash, Rockmore, and Uppal (2019), Castelló-Climent et al. (2018), Jha and Talathi (2021).

One issue with the ‘stable’ nightlights data product is that it is top-coded at a DN of 63 and bottom-censored at a DN of 0. The top-coding and bottom-censoring prevalent in the ‘stable’ nightlights data product limits variation in intensities of nighttime lights across the brightest and dimmest areas.¹² In light of this, we obtain nighttime lights data for the years 1993 and 2001 from Bluhm and Krause (2022) (BK hereon) who correct the ‘stable’ nighttime lights images for top-coding and bottom-censoring.¹³ Ideally, nighttime lights data from the pre-liberalization period, such as 1987 or 1990, would be better suited for our analysis, however, they are only available starting in 1992. Following Jha and Talathi (2021) who cite issues related to the quality of the 1992 nighttime lights data, we use data from 1993 instead as a proxy for pre-liberalization development levels.

We superimpose the 1991-district boundary shapefile of India with the respective nighttime lights images in ArcGIS and obtain the *sum of lights* statistic for 1993 and 2001 for each district.^{14,15} This statistic represents the total intensity of nighttime lights emitted from each district. We divide this statistic by the district population to obtain the *Nightlights Per Capita* measure which serves as our proxy for per capita income at the district level.¹⁶ Figure 1A shows the 1993 raw image of nighttime lights in India and Figure 1B shows the same for 2001. It is apparent from a visual inspection of these figures that nighttime lights increased significantly over this period. Figures 2A and 2B show the distribution of nightlights per capita in 1993 and 2001 across districts in India, respectively. It turns out that on average nightlights per capita increased by 47% during this period. Some studies, such as Henderson et al. (2012), Castelló-Climent et al. (2018), and Chor and Li (2021) use *Nightlights Density* (Nightlights Per Area) instead as a proxy for economic activity. In light of this, we replicate our baseline results with *Nightlights Density* as

¹² See Jha and Talathi (2021), Henderson et al. (2012), Pinkovskiy and Sala-i-Martin (2016), Chanda and Kabiraj (2020), and Prakash, Rockmore, and Uppal (2019) for more information on the top-coding and bottom-censoring issue prevalent in the ‘stable’ nighttime lights data product.

¹³ The EOG maintains the Global Radiance Calibrated Nighttime Lights (RC hereon) data product which also corrects for the top-coding issue. The RC data product is however only available for years 1996, 1999, 2000, 2003, 2004, 2006, and 2010. Since we are interested in data closer to the 1991 trade liberalization reform, we resort to the BK nighttime lights data that corrects for top-coding for all years (1992 – 2013). We use the BK corrected images of nighttime lights captured by the newer satellites in 1993 and 2001. The BK nighttime lights data was retrieved on Nov 15, 2022 from <https://lightinequality.com/top-lights>.

¹⁴ We obtain the 1991 district boundary shapefile from IPUMS International GIS Boundary Files (IPUMS hereon). The 1993 district boundary shapefile in IPUMS is consistent with the 1991 Census district boundaries of India.

¹⁵ Our choice of terminal year 2001 is to allow for a few years gap between the tariff of 1997 and the nighttime lights. The results are robust to using nighttime lights data from another year close to 2001.

¹⁶ We use 1991 and 2001 district-level population to compute *Nightlights Per Capita* in 1993 and 2001 respectively. The 1991 and 2001 district-level population were obtained from the 1991 and 2001 Census of India respectively. We refer to Kumar and Somanathan (2009) and <http://www.statoids.com/yin.html> in matching the 2001 district boundaries to the 1991 district boundaries. We are thus able to obtain the 2001 district population for all the 466 districts (as per the 1991 district boundaries). See Jha and Talathi (2021) for more information on the methodology used to obtain *Nightlights Per Capita*.

the dependent variable and validate the robustness of our main results. Figures 3A and 3B show the variation in *Nightlights Density* across districts in India.¹⁷ There is an increase of 77% in the average *Nightlights Density* over this period which is much larger than the increase in nightlights per capita because the area remained fixed while the population grew rapidly over this period.

III.2 Trade Liberalization Data

We obtain district-level data on tariffs and non-tariff barriers from Topalova (2007, 2010). From publications of the Ministry of Finance, India, Topalova (2007, 2010) has manually digitized detailed tariffs at the 6-digit level of the Indian Trade Classification Harmonized System (HS) for approximately 5000 product lines. She obtains a measure of average sector-level tariffs by matching the 5000 product lines to the NIC codes using the concordance of Debroy and Santhanam (1993). Topalova (2010) compiles data on Non-Tariff Barriers (NTBs) for 1997 (post-reform period) from the publication EXIM Policy, Directorate General of Foreign Trade, India. The NTBs measure is constructed as the share of products within a production sector that can be imported without any license. At the district level, the NTBs measure is an average weighted by the industry-specific employment share in that district.

IV. Empirical Specification and Results

IV.1 Estimation Strategy

We use a simple two-way fixed effects model (district and time fixed effects) to identify the effects of trade liberalization on local development. Our key estimating equation is below.

$$y_{d,t} = \alpha + \beta \text{Tariff}_{d,t} + \delta_d + \text{POST}_t + \varepsilon_{d,t} \dots\dots\dots (1)$$

where $y_{d,t}$ is the natural log of nightlights per capita for district d in year t , $\text{Tariff}_{d,t}$ is the district level tariff in year t , δ_d is the district fixed effect and POST_t is the time fixed effect. A positive estimate of β will indicate that districts experiencing greater trade liberalization

¹⁷ We use the area of each district in 1991 to compute *Nightlights Density* in 1993 and 2001. We obtain the area of each district from the 1991 Census of India.

experienced smaller increases in nightlights per capita while a negative estimate of β will indicate the opposite.

We use district-level tariff data from Topalova (2007, 2010) which is constructed as the average of industry-level tariffs weighted by the industry-specific employment shares of that district in 1991 as shown in equation 2 below.¹⁸

$$Tariff_{d,t} = \sum_i \gamma_{i,d,1991} * Tariff_{i,t} \quad (2)$$

In equation (2), $\gamma_{i,d,1991}$ represents the industry (i) specific employment shares in district d in 1991.

This is computed as $\gamma_{i,d,1991} = \frac{Workers_{i,d,1991}}{Workers_{d,1991}}$ where $Workers_{d,1991}$ is all workers in district d .

Since the industry-specific employment shares are available separately for the rural and urban parts of a district, Topalova (2007) computes rural and urban tariffs for each district separately.¹⁹ Our tariff for a district is the weighted average of the rural and urban tariffs for the district where weights are the shares of the rural and urban population, respectively, in the district in 1991.

While $Tariff_{d,t}$ correctly measures the inverse exposure of a district to trade in the sense that higher $Tariff_{d,t}$ implies less exposure, since non-traded goods are assigned a tariff of zero in this calculation, a causal interpretation of the effect of trade liberalization on development using this measure may be problematic for reasons discussed in detail in Topalova (2010). For example, a poor district may have a large share of workers in the non-traded sector resulting in a lower tariff in the initial period and a smaller trade liberalization (since tariffs were reduced in such a way to bring them to a uniform level). Now, if poorer districts tend to grow faster leading to convergence (a result that we verify in our context)²⁰, even in the absence of a causal effect of trade liberalization our OLS estimates will show that districts with lower trade liberalization grew faster suggesting a negative effect of trade liberalization on development (a positive β coefficient).²¹ Therefore, following Topalova (2010) we use $TrTariff_{d,t}$ which is calculated by ignoring the workers in the non-traded sector:

¹⁸ In this measure, the non-traded industries (services, trade, transport, and cultivation of cereals and oilseeds) are assigned a zero tariff for the entire period (Topalova, 2010).

¹⁹ We thank Petia Topalova for sharing her tariffs data with us.

²⁰ See the regression in column 1 in the online appendix Table A1 which shows that initially poorer districts grew faster. The convergence coefficient is -.022.

²¹ In column 2 in the online appendix Table A1 we verify that districts with lower initial nightlights per capita experienced smaller changes in tariffs.

$$TrTariff_{d,t} = \sum_i \gamma_{i,d,1991} * Tariff_{i,t} \quad (3)$$

where $\gamma_{i,d,1991} = \frac{Workers_{i,d,1991}}{\sum_i Workers_{i,d,1991}}$, that is the denominator includes only workers in the traded sectors rather than all workers.²² Since this measure does not depend on the share of workers in the non-traded sector and is highly correlated with $Tariff_{d,t}$, we use it as an instrument for $Tariff_{d,t}$. The first stage results are shown in Appendix Table A1 where $Tariff_{d,t}$ is regressed on $TrTariff_{d,t}$ in column 3 and $TrTariff_{d,t}$ and its interaction with the dummy for the post-trade liberalization year in column 4. The coefficients of $TrTariff_{d,t}$ and its interaction with the post-liberalization time dummy are large and highly significant in both columns.

IV.2 Empirical Results

Our baseline results are presented in Table 2. In column 1 the OLS coefficient of $Tariff_{d,t}$ is positive but insignificant. As mentioned earlier, given that we find convergence in nightlights per capita across districts and the fact that poorer districts experienced smaller declines in tariffs, this by itself would suggest a positive β . In column 2 we regress nightlights per capita on $TrTariff_{d,t}$ which can be considered a reduced form regression as we are going to use $TrTariff_{d,t}$ as an instrument for $Tariff_{d,t}$. We find a strong negative relationship between $TrTariff_{d,t}$ and nightlights per capita suggesting that districts experiencing greater trade liberalization had a larger increase in nightlights per capita. Column 3 presents the first *IV* results and here we find the estimate of β to be negative and significant suggesting a causal relationship between trade liberalization and nightlights per capita. That is, districts with greater trade liberalization experienced more rapid increases in nightlights per capita. Since the average decline in tariffs was 6.9 percentage points²³, the coefficient of $Tariff_{d,t}$ in column 3 of -1.78 implies a $.069 * 1.78$ increase in log nightlights per capita or 13% increase in nightlights per capita. Using an estimate of the elasticity of GDP per capita with respect to nightlights per capita

²²Again, our traded tariff is a weighted average of the traded rural tariff and the traded urban tariff for the district.

²³ In Topalova (2010) the average decline in rural tariffs is 5.5 percentage points which is lower than the average decline in combined (rural and urban) tariff of 6.9 percentage points.

of 0.22, this translates into 2.86% more GDP per capita. That is, districts that experienced a 6.9% decline in tariffs experienced a relative increase in GDP of 2.86%.

To alleviate the concern that changes in tariffs may be correlated with time-varying shocks that affect the level of development, in column 4 we include some initial district conditions interacted with the post-liberalization time dummy.^{24,25} The coefficient of $Tariff_{d,t}$ goes down but remains negative and highly significant. In column 5 we add non-tariff barriers as an additional regressor. The coefficient of $Tariff_{d,t}$ goes down in magnitude but remains large and negatively significant. As argued by Topalova (2010), non-tariff barriers were removed more slowly and varied a lot across goods, therefore, their inclusion should be regarded as a robustness exercise and the coefficient of NTBs should not be given a causal interpretation.

Since trade liberalization was not the only reform, our estimates may be picking up the effects of some other reforms such as delicensing, liberalization of FDI, and banking reforms. In column 6 we include these time-varying measures of reforms.²⁶ Compared to column 4, the coefficient of $Tariff_{d,t}$ does not change much. Finally, in column 7 we instrument $Tariff_{d,t}$ using both $TrTariff_{d,t}$ and its interaction with the post-liberalization time dummy. The coefficient of $Tariff_{d,t}$ drops in magnitude but remains negative and significant.

While we have used nightlights per capita as our proxy for development as is more common in the literature, some papers use nightlight density measured by the sum of nightlights divided by the area of the region as a proxy for development. In Table A2 in the appendix, we replicate all the regressions reported in Table 2 by replacing the dependent variable with nightlight density. The results are very similar to those reported in Table 2.

While we included $TrTariff_{d,t}$ as the measure of tariff in column 2 of Table 2 and called it our reduced form regression, Hasan et al. (2007) use this as their measure of tariff in their estimation using state-level data. For comparison with Hasan et al. (2007) as well as to show the

²⁴ Among other things, this concern arises because district level tariffs are constructed using occupational weights at the district level and the initial occupational characteristics of a district could have a bearing on their subsequent growth.

²⁵ Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). We use these variables from Topalova (2010).

²⁶ Data on FDI and Industry Licensing are obtained from Topalova (2010) who in turn compiles the data from various publications of the Handbook of Industrial Statistics. FDI is an indicator variable that takes the value of 1 if the industry is in the list of industries with automatic permission for foreign equity share up to 51 percent at time t. License is also an indicator variable that takes the value of 1 if the industry is subject to licensing requirements at time t. At the district-level, both these measures are an average weighted by the industry specific (mining and manufacturing) employment share in that district respectively. Data on bank branches per capita are obtained from Topalova (2010) which in turn is created from the Directory of Commercial Bank Offices in India (Volume 1), Reserve Bank of India, 2000.

robustness of our results to this alternative measure of tariff, in appendix Table A3 we report the results when we include initial district characteristics as well as controls for other reforms. The coefficient of $TrTariff_{d,t}$ is negative and significant in all cases as shown in the first 4 columns of Table A3.

Next, we look at some channels through which trade liberalization may affect development. This will also allow us to study if the local effects of trade liberalization are heterogeneous.

IV.3 Heterogeneous Effects of Trade Liberalization

Both Topalova (2010) and Hasan et al. (2007) found that the impact of trade liberalization on poverty varied depending on whether a state had flexible or rigid labor laws. Using Besley and Burgess's (2004) classification of states into flexible and non-flexible with regard to labor laws where the dummy Flexible Labor Laws takes the value 1 for flexible law states and 0 otherwise, we add an interaction of this dummy to $Tariff_{d,t}$ and report the results in columns 1 and 2 of Table 3.²⁷ Column 1 adds this interaction to the regression reported earlier in column 6 of Table 1 where $Tariff_{d,t}$ was instrumented by $TrTariff_{d,t}$. The interaction coefficient in column 1 of Table 3 is negative. This along with the coefficient of $Tariff_{d,t}$ itself implies that the impact of trade liberalization on nightlights per capita is much larger in districts in states with flexible labor laws compared to districts in other states. A similar result is obtained in column 2 when $Tariff_{d,t}$ is instrumented by $TrTariff_{d,t}$ and its interaction with the post-liberalization dummy.

Next, we test if the impact of trade liberalization varies according to the distance from the coast.²⁸ The motivation behind using this variable is that proximity to the coast will reduce the cost of trading goods internationally and, therefore, the impact of trade liberalization on domestic prices could differ across districts depending on their proximity to the coast. As a consequence, trade liberalization can have differential effects on districts depending on their proximity to the coast. The results reported in columns 3 and 4 of Table 3 suggest that the positive effect of trade liberalization on nightlights per capita is larger the shorter the distance from the coast. Based on

²⁷ Following Topalova (2010), we assign a value of 0 (having neutral labor legislation) to smaller states that are not covered in Besley and Burgess (2004).

²⁸ Using the coastal boundary shapefile of India from Natural Earth Data we compute the distance to the nearest coastline (decimal degrees) from the centroid of each district in ArcGIS.

the estimated coefficients in column 3 we can conclude that a 6.9 percentage points reduction in tariffs at a district on the coast leads to a relative increase of 24.6% increase in nightlights per capita.²⁹

Next, we look at the implications of road length per capita and railroad length per capita and report the results in columns 5 to 8 of Table 3.³⁰ For road length per capita, the coefficients in columns 5 and 6 imply that the larger the road length per capita the greater the positive effect of trade liberalization on nightlights per capita. The coefficients in column 5 imply that the impact of trade liberalization on nightlights per capita is positive as long as the road length per capita exceeds -0.46 standard deviation below the mean.³¹ Hasan et al. (2007) find that trade liberalization has a larger negative effect on poverty in states with a greater density of roads. This is broadly consistent with our finding of trade liberalization having a larger positive effect on nightlights per capita in districts with greater road length per capita. The coefficients of the interaction between $Tariff_{d,t}$ and railroad length per capita reported in columns 7 and 8 are positive. The positive sign implies that a better railroad network reduces the benefit of trade liberalization, however, the impact of trade liberalization on nightlights per capita remains positive.³²

Finally, we use the female labor force participation rate which is a strong correlate of development and remains very low in India compared to other countries at similar levels of development. While the average rate of 38% is quite low, it varies from an abysmally low rate of 3% to a high rate of 84%.³³ We use the interaction of female labor participation rate with $Tariff_{d,t}$ as an additional regressor and report the results in columns 9 and 10 of Table 3. In both cases the interaction coefficient is negative and significant suggesting that trade liberalization is beneficial for districts with high rates of female labor force participation. A similar result is obtained when we use the share of females in the workforce.

Note that all the regressions in Table 3 include initial district characteristics interacted with post liberalization dummy and other reform controls. The results when we do not include

²⁹ For a district on the coast, the distance from the coast is zero and hence the coefficient of tariffs is simply -3.19 which translates into $-3.19 * .069 = 0.22$ increase in log of nightlights per capita.

³⁰ We import raw vector (line) data for roads and railroads from DIVA-GIS into ArcGIS and obtain the total length (km) of roads and railroads for each district as of 1992. The total length of roads and railroads is then divided by the population to obtain road length per capita and railroad length per capita.

³¹ We use standardized values of road length per capita and railroad length per capita to facilitate comparison.

³² The coefficient of the interaction term in column 7 implies that the impact of trade liberalization on nightlights per capita is positive as long as the railroad length per capita in the district is less than 2 standard deviation above the mean.

³³ This data is obtained from the 1991 Census of India and is for females above the age of 15.

other reforms are presented in Table A4 in the appendix and are qualitatively similar to those presented in Table 3. Also, when we use nightlight density as an alternative measure of development and replicate the regressions in Table 3 and appendix Table A4, we get very similar results. That is, all our results presented in the paper are robust to the use of nightlight density as the dependent variable.

V. Concluding Remarks

We have studied the local effects of a large episode of trade liberalization in India starting in 1991 using nightlights per capita as a proxy for overall development at the district level. Our results suggest that on average trade liberalization increased nightlights per capita in districts across India but there was considerable heterogeneity in the effect. In particular, districts in states with flexible labor laws or districts with better road networks or proximity to the coast, or higher female labor force participation rates seem to have benefited more compared to other districts.

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Figure 1A: Raw image of nighttime lights in 1993 for India

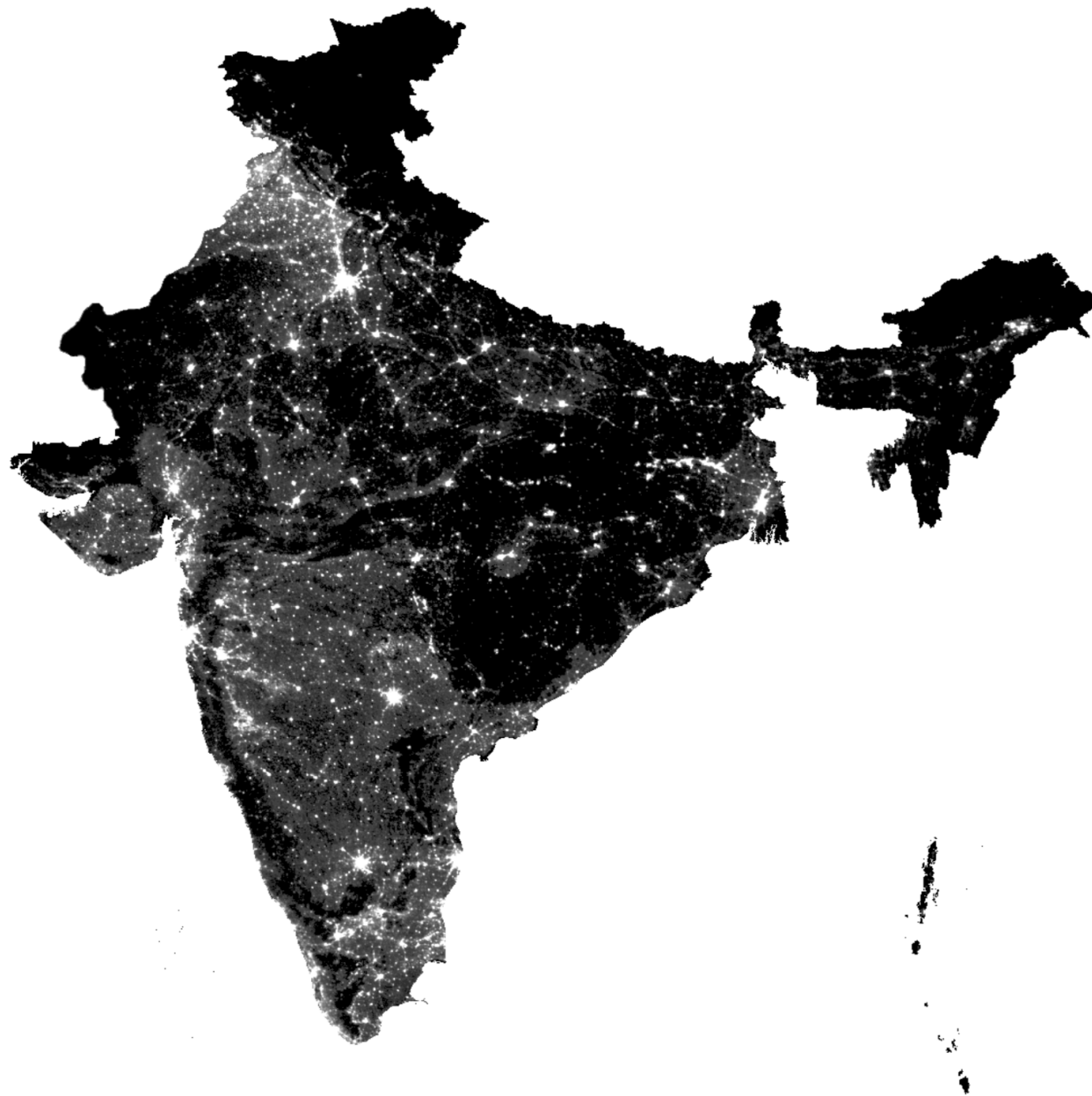


Figure 1B: Raw image of nighttime lights in 2001 for India

Log Lights Per Capita in 1993

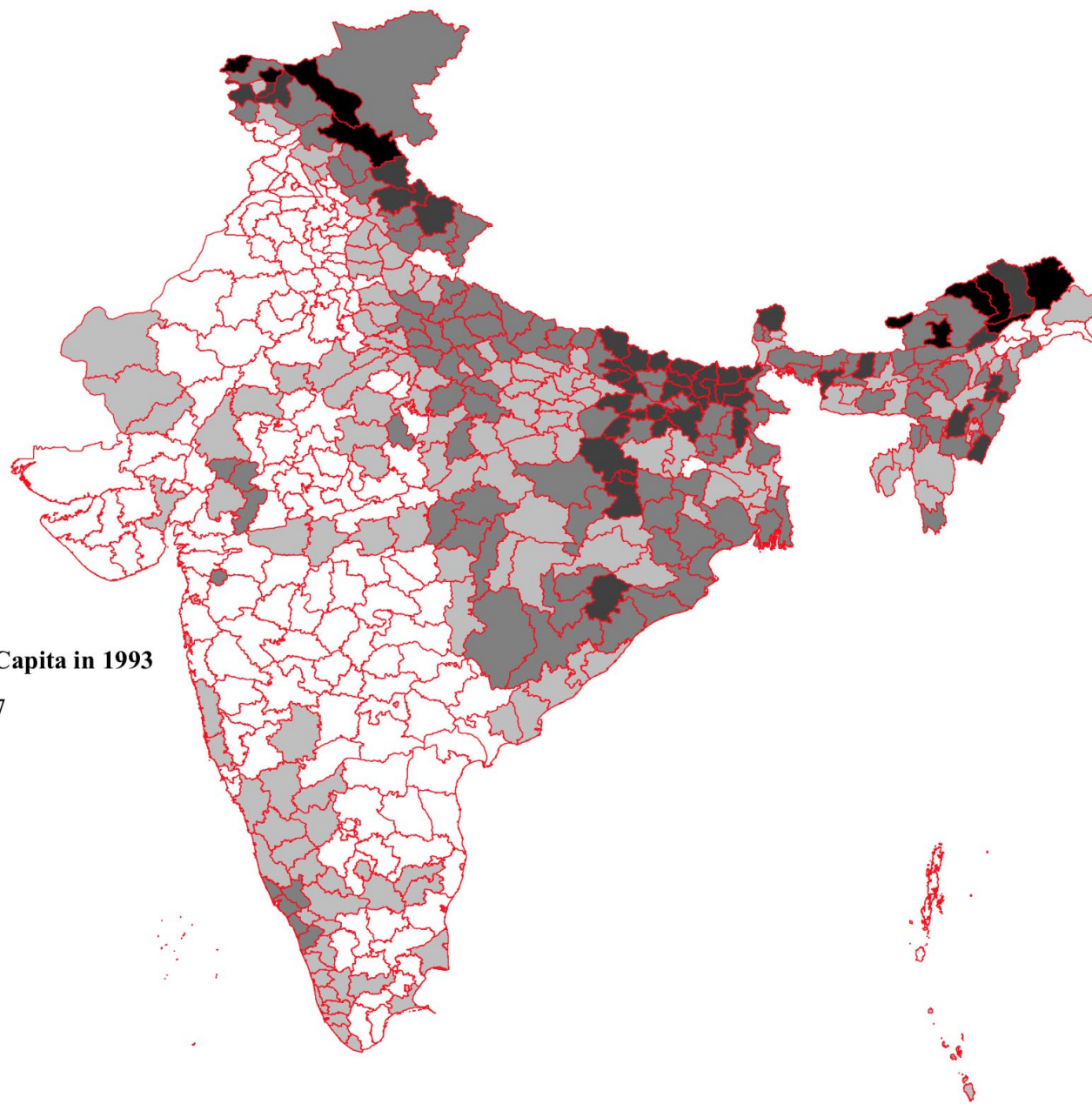
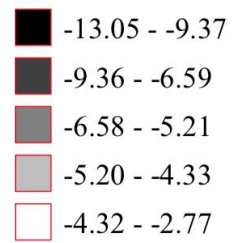


Figure 2A: Distribution of log lights per capita in 1993 across districts in India

Log Lights Per Capita in 2001

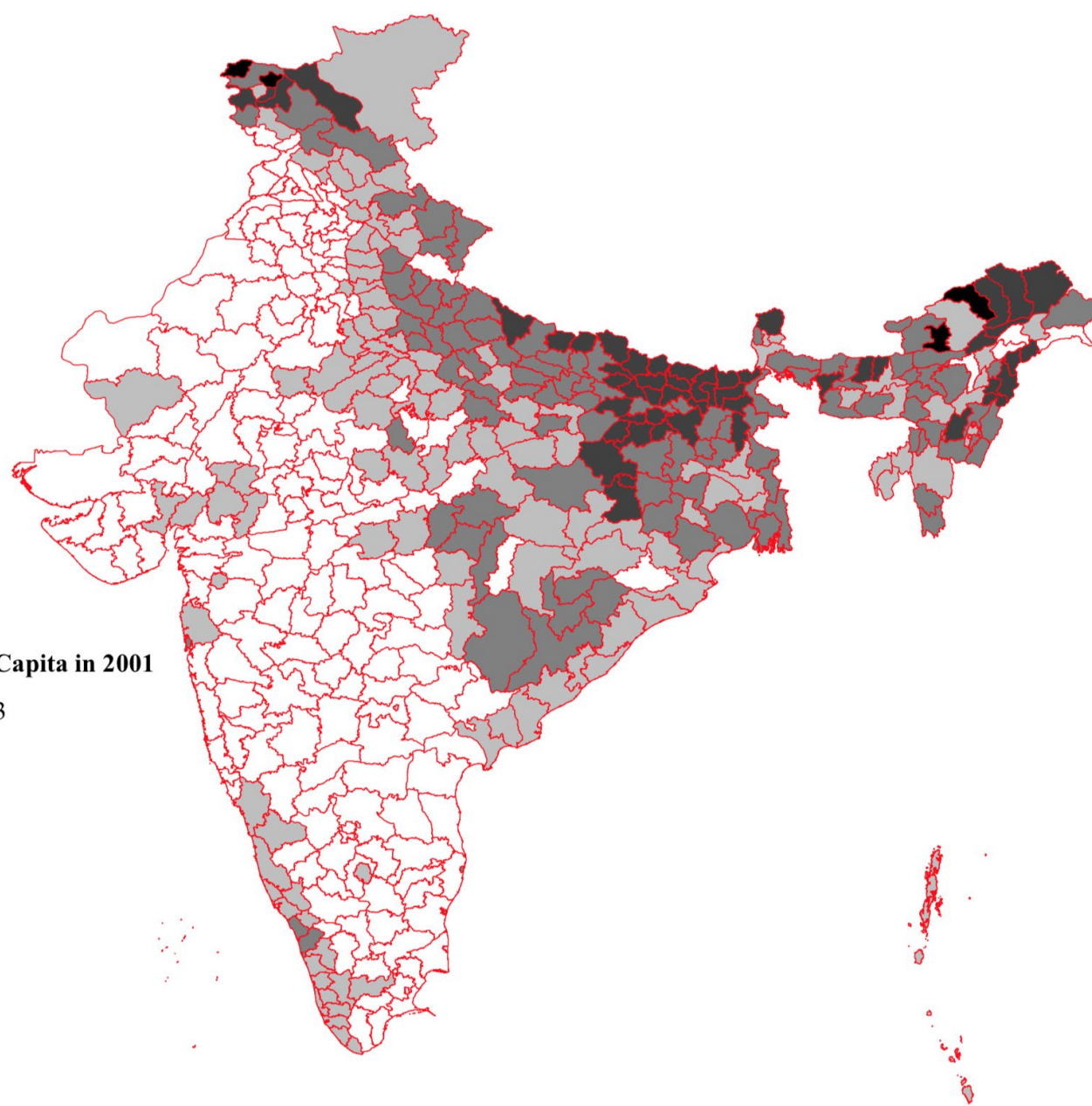
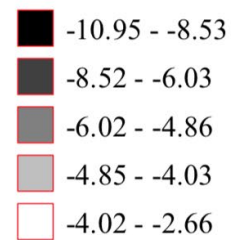


Figure 2B: Distribution of log lights per capita in 2001 across districts in India

Log Lights Density in 1993

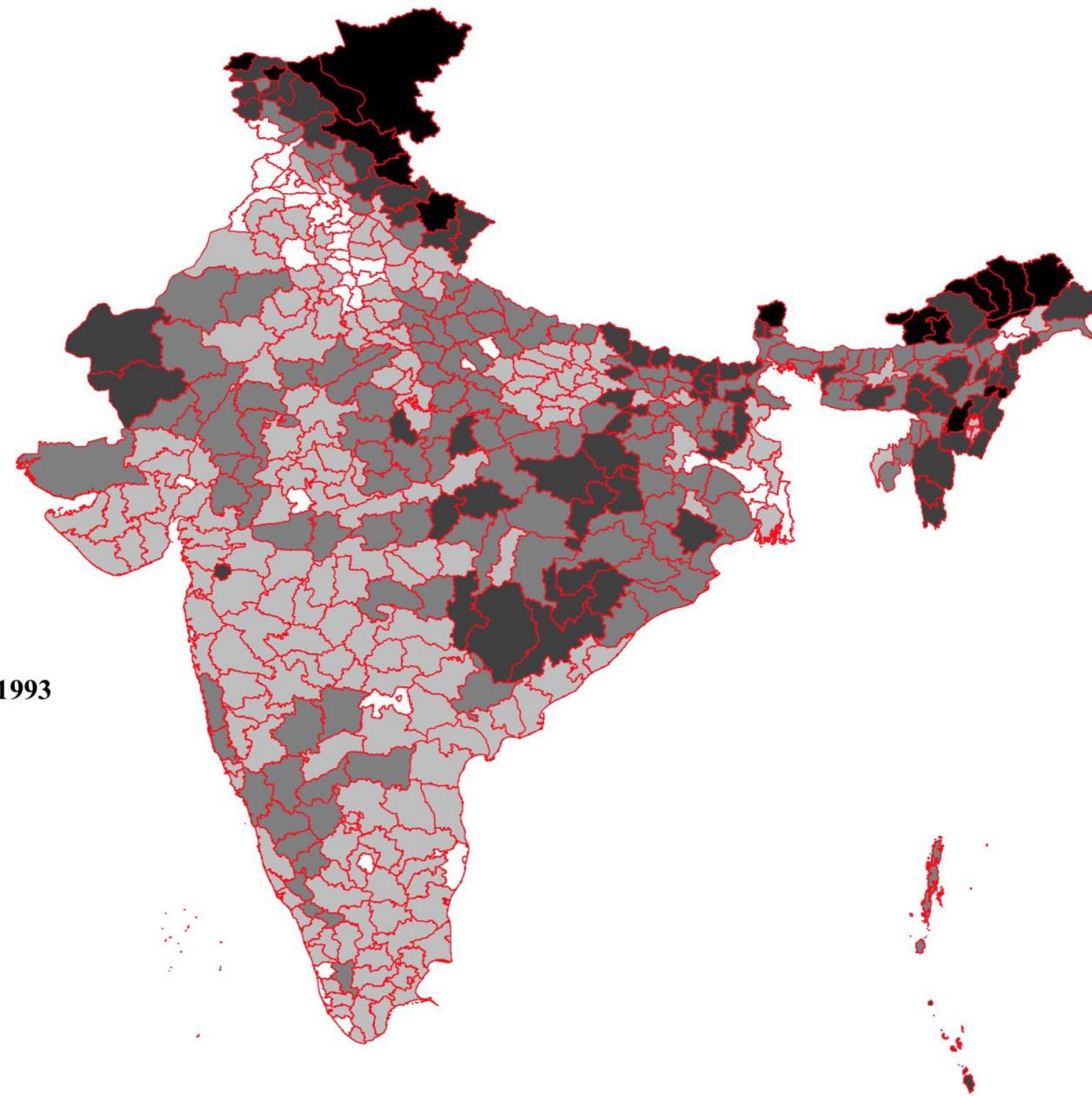
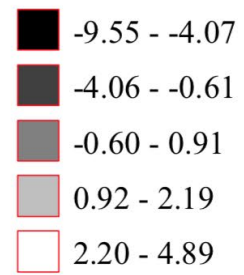


Figure 3A: Distribution of log lights density in 1993 across districts in India

Log Lights Density in 2001

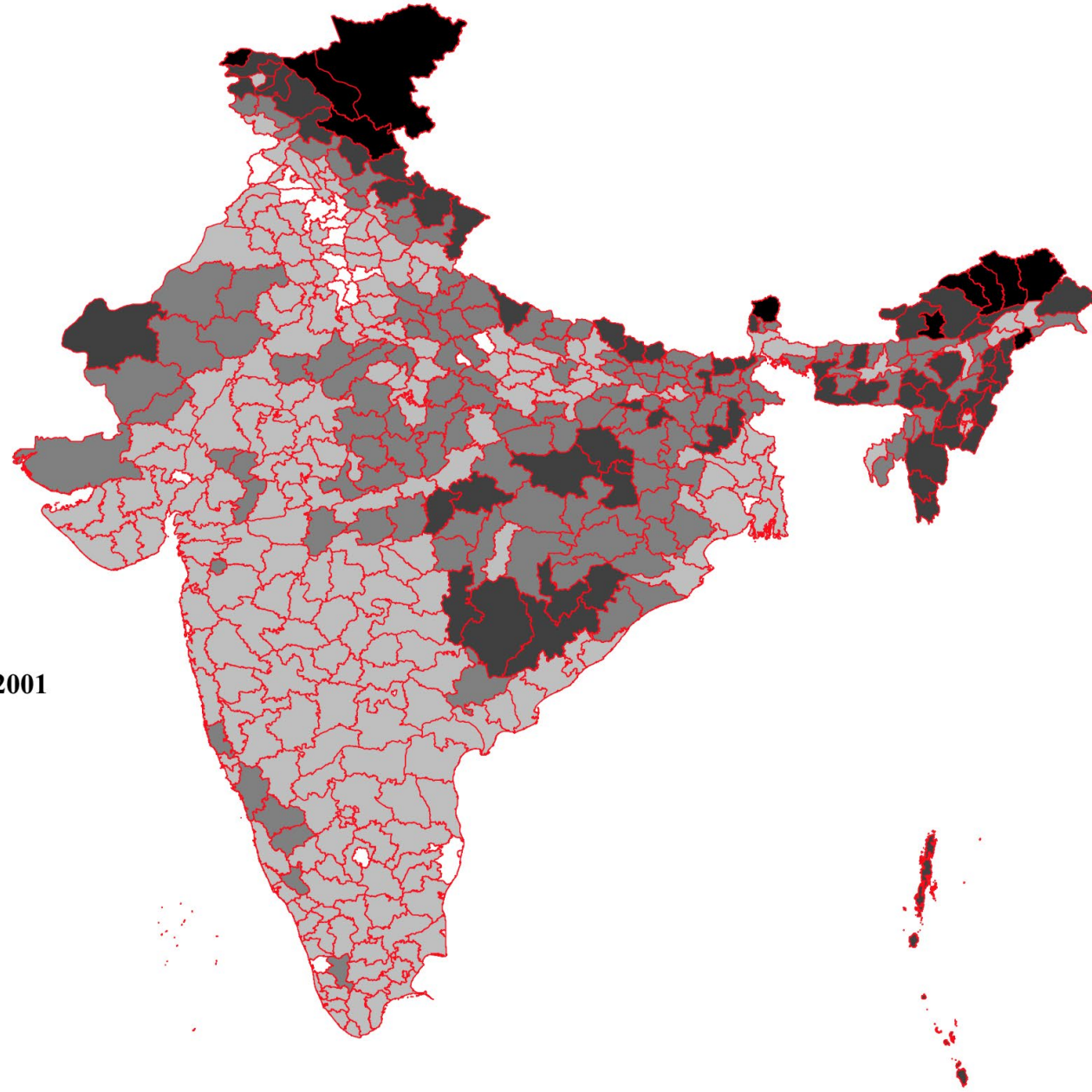
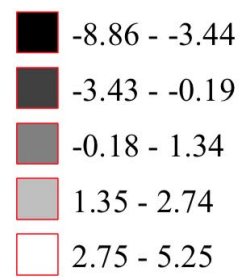


Figure 3B: Distribution of log lights density in 2001 across districts in India

Table 1: Summary Statistics

Variable	Pre-Reform			Post-Reform		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Log Lights Per Capita	394	-4.859	1.093	394	-4.477	0.990
Log Lights Density	394	0.830	1.329	394	1.402	1.076
Tariff	394	0.103	0.079	394	0.034	0.024
Traded Tariff	394	0.888	0.081	394	0.306	0.056
NTBs	394	0.010	0.016	394	0.036	0.039
Sh. Industries open to FDI	394	0.000	0.000	394	0.213	0.113
Sh. Industries subject to Licensing Requirements	394	0.341	0.159	394	0.091	0.153
Number of Banks Per Capita (Per 10,000 People)	394	0.635	0.249	394	0.768	0.309
Sh. Literate Population	394	0.367	0.133			
Sh. Population belonging to SC or ST	394	0.287	0.156			
Sh. Workers in Agriculture	394	0.816	0.098			
Sh. Workers in Manufacturing	394	0.054	0.042			
Sh. Workers in Mining	394	0.005	0.013			
Sh. Workers in Trade	394	0.032	0.019			
Sh. Workers in Transport	394	0.013	0.011			
Sh. Workers in Service	394	0.066	0.037			
Sh. Workers in Construction	394	0.012	0.013			
Flexible Labor Laws	394	0.376	0.485			
Distance to Coast (decimal degrees)	394	4.173	3.032			
Log Road Length Per Capita	394	-7.549	0.699			
Log Railroad Length Per Capita	394	-8.961	1.186			
Female Labor Force Participation Rate	394	0.379	0.189			

Note: The summary statistics presented for log road length per capita, log railroad length per capita, and female labor force participation rate are for the non-standardized measures of these variables. We use the standardized measures (mean of 0 and std. dev. of 1) of these variables in our regressions.

Table 2: Effect of Trade Liberalization on Local Development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log lights per capita							
Tariff	0.614 (0.534)		-1.778** (0.695)	-1.163*** (0.398)	-0.900** (0.357)	-1.318*** (0.440)	-0.950*** (0.324)
Traded Tariff		-0.667** (0.310)					
NTBs					-2.116*** (0.632)		
R-squared	0.956	0.956	0.951	0.972	0.973	0.973	0.973
Observations	788	788	788	788	788	788	788
IV with traded tariff	NO	NO	YES	YES	YES	YES	NO
IV with traded tariff and initial traded tariff × post	NO	NO	NO	NO	NO	NO	YES
Initial district conditions × post	NO	NO	NO	YES	YES	YES	YES
Other Reform Controls	NO	NO	NO	NO	NO	YES	YES

Note: Standard errors are clustered at the state-year level. We include district and year fixed-effects in all the columns. Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). Other reform controls include share of license-industries, share of industries open to foreign direct investment (FDI), and number of bank branches per capita. Similar to the construction of district-level tariffs, the share of license-industries and share of industries open to FDI are weighted by the respective employment shares in each district.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Heterogeneous Effects of Trade Liberalization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: log lights per capita										
Tariff	-1.016*	-0.661	-3.190***	-2.167***	-1.017**	-0.514	-1.131***	-0.688**	-0.470	0.328
	(0.529)	(0.442)	(0.491)	(0.286)	(0.487)	(0.360)	(0.421)	(0.340)	(0.565)	(0.455)
Tariff × Flexible Labor Laws	-0.808	-0.784								
	(0.575)	(0.614)								
Tariff × Dist. to Coast			0.609***	0.569***						
			(0.115)	(0.120)						
Tariff × Road Length Per Capita					-2.205***	-2.195***				
					(0.492)	(0.518)				
Tariff × Railroad Length Per Capita							0.569*	0.231		
							(0.343)	(0.161)		
Tariff × Female Labor Force Participation Rate									-2.083***	-1.989***
									(0.532)	(0.511)
R-squared	0.973	0.974	0.975	0.976	0.973	0.973	0.972	0.974	0.972	0.973
Observations	788	788	788	788	788	788	788	788	788	788
IV with traded tariff	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
IV with traded tariff and initial traded tariff × post	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: Standard errors are clustered at the state-year level. All columns include district fixed-effects, year fixed-effects, initial district conditions × post, and other reform controls. Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). Other reform controls include share of license-industries, share of industries open to foreign direct investment (FDI), and number of bank branches per capita. Similar to the construction of district-level tariffs, the share of license-industries and share of industries open to FDI are weighted by the respective employment shares in each district. Flexible Labor Laws is an indicator variable that takes a value of 1 if labor laws in a state are pro-employer (Topalova, 2010; Besley and Burgess, 2004). Distance to Coast is measured in decimal degrees. We use the natural log of road length per capita and railroad length per capita as our measures of physical infrastructure. The physical infrastructure variables as well as female labor force participation rate are standardized to have a mean of 0 and a standard deviation of 1.

*** p<0.01, ** p<0.05, * p<0.1

Table A1: Convergence, Correlation between Change in Tariff and Initial Level of Development, and First-Stage Results

	(1)	(2)	(3)	(4)
	Convergence	Δ in Tariffs and Initial Dev. Level	First-Stage	
	Dependent Variable:			
	Growth in Lights Per Capita	Abs. Δ in Tariffs	Tariff	Tariff
Log Lights Per Capita in 1993	-0.0217** (0.00970)	0.0167*** (0.00377)		
Traded Tariff			0.375*** (0.0778)	0.567*** (0.115)
Initial Traded Tariff \times Post				0.232*** (0.0744)
R-squared	0.180	0.099	0.857	0.865
Observations	394	394	788	788
Cross-sectional regression	YES	YES	-	-
Panel regression	-	-	YES	YES
District FE	-	-	YES	YES
Year FE	-	-	YES	YES

Note: Standard errors are clustered at the state level in columns 1 and 2 and at the state-year level in columns 3 and 4. Dependent variable in column 1 is the growth in nighttime lights per capita from 1993 to 2001. Dependent variable in column 2 is the absolute change in tariffs from 1987 to 1997.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A2: Robustness of Main Results (Log Lights Density as Dependent Variable)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: log lights density (log lights per area)							
Tariff	0.831 (0.495)		-1.669** (0.712)	-1.366*** (0.439)	-1.079*** (0.383)	-1.473*** (0.481)	-0.960*** (0.338)
Traded Tariff		-0.626* (0.317)					
NTBs					-2.311*** (0.495)		
R-squared	0.970	0.970	0.967	0.981	0.981	0.981	0.981
Observations	788	788	788	788	788	788	788
IV with traded tariff	NO	NO	YES	YES	YES	YES	NO
IV with traded tariff and initial traded tariff × post	NO	NO	NO	NO	NO	NO	YES
Initial district conditions × post	NO	NO	NO	YES	YES	YES	YES
Other Reform Controls	NO	NO	NO	NO	NO	YES	YES

Note: Standard errors are clustered at the state-year level. We include district and year fixed-effects in all the columns. Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). Other reform controls include share of license-industries, share of industries open to foreign direct investment (FDI), and number of bank branches per capita. Similar to the construction of district-level tariffs, the share of license-industries and share of industries open to FDI are weighted by the respective employment shares in each district.

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Robustness of Main Results (Traded Tariff as Independent Variable)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: log lights per capita									
Traded Tariff	-0.667** (0.310)	-0.448** (0.189)	-0.381* (0.197)	-0.507** (0.202)	-0.342 (0.214)	-0.749*** (0.245)	-0.424** (0.185)	-0.520*** (0.172)	-0.332 (0.253)
NTBs			-1.402 (0.936)						
Traded Tariff × Flexible Labor Laws					-0.643* (0.347)				
Traded Tariff × Dist. to Coast						0.0714*** (0.0163)			
Traded Tariff × Road Length Per Capita							-0.271*** (0.0656)		
Traded Tariff × Railroad Length Per Capita								0.0816 (0.0506)	
Traded Tariff × Female Labor Force Participation Rate									-0.191*** (0.0616)
R-squared	0.956	0.973	0.973	0.974	0.974	0.976	0.976	0.975	0.976
Observations	788	788	788	788	788	788	788	788	788
Initial district conditions × post	NO	YES	YES	YES	YES	YES	YES	YES	YES
Other Reform Controls	NO	NO	NO	YES	YES	YES	YES	YES	YES

Note: Standard errors are clustered at the state-year level. We run reduced form OLS regressions with district and year fixed-effects in all columns. Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). Other reform controls include share of license-industries, share of industries open to foreign direct investment (FDI), and number of bank branches per capita. Similar to the construction of district-level tariffs, the share of license-industries and share of industries open to FDI are weighted by the respective employment shares in each district. Flexible Labor Laws is an indicator variable that takes a value of 1 if labor laws in a state are pro-employer (Topalova, 2010; Besley and Burgess, 2004). Distance to Coast is measured in decimal degrees. We use the natural log of road length per capita and railroad length per capita as our measures of physical infrastructure. The physical infrastructure variables as well as female labor force participation rate are standardized to have a mean of 0 and a standard deviation of 1.

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Heterogeneous Effects of Trade Liberalization (without other reform controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: log lights per capita										
Tariff	-1.097*	-0.841*	-2.959***	-1.943***	-0.826	-0.433	-0.945**	-0.579	-0.271	0.513
	(0.569)	(0.494)	(0.462)	(0.277)	(0.518)	(0.421)	(0.450)	(0.358)	(0.535)	(0.475)
Tariff × Flexible Labor Laws	-0.176	-0.206								
	(0.594)	(0.666)								
Tariff × Dist. to Coast			0.576***	0.525***						
			(0.109)	(0.118)						
Tariff × Road Length Per Capita					-2.244***	-2.222***				
					(0.530)	(0.545)				
Tariff × Railroad Length Per Capita							0.671*	0.207		
							(0.396)	(0.163)		
Tariff × Female Labor Force Participation Rate									-2.304***	-2.171***
									(0.599)	(0.571)
R-squared	0.972	0.973	0.974	0.975	0.972	0.972	0.971	0.973	0.972	0.972
Observations	788	788	788	788	788	788	788	788	788	788
IV with traded tariff	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
IV with traded tariff and initial traded tariff × post	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: Standard errors are clustered at the state-year level. All columns include district fixed-effects, year fixed-effects, and initial district conditions × post. Initial district characteristics include share of literate population, share of population belonging to scheduled caste or schedule tribe, and share of workers in agriculture, manufacturing, mining, trade, transport, and services (share of workers in construction is treated as the omitted category). Flexible Labor Laws is an indicator variable that takes a value of 1 if labor laws in a state are pro-employer (Topalova, 2010; Besley and Burgess, 2004). Distance to Coast is measured in decimal degrees. We use the natural log of road length per capita and railroad length per capita as our measures of physical infrastructure. The physical infrastructure variables as well as female labor force participation rate are standardized to have a mean of 0 and a standard deviation of 1.

*** p<0.01, ** p<0.05, * p<0.1