And There Was Light: Trade and the Development of Border Regions[*]

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Abstract

Does international trade help or hinder the economic development of border regions? Theory tends to suggest that trade helps, but it can also predict the reverse. We estimate how changes in bilateral trade volumes affect economic activity along roads running inland from international borders, using satellite night-light measurements for up to 1,799 border-crossing roads worldwide. We observe a significant 'border shadow': on average, lights are 18 percent dimmer within 50 kilometers of the border than further inland. We find this difference to be reduced by trade expansion as measured by exports and instrumented with asymmetric tariff changes on the opposite side of the border. In our baseline estimate, a 10% increase in exports to a particular neighbor country is associated with a brightening of lights by some 2.8 percent at the border, but by only 1.6 percent 300 kilometers inland. We provide evidence that local export-oriented production is a significant mechanism behind the observed effect. Our empirical results can also shed light on equilibrium properties in a variety of spatial models.

JEL Classification: F14, F15, R11, R12

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1 Introduction

In most countries, locations close to land borders are less economically developed than interior or coastal locations. Border regions are literally darker: night lights captured by satellites are on average 18 percent less intense within 50 kilometers of international land borders than further inland.[1] Such 'border shadows' are both a cause and a consequence of national boundaries. On the one hand, country borders often run through naturally inhospitable regions such as mountain ranges or deserts.[2] On the other hand, borders themselves segment markets and thereby act as an impediment to regional economic development. In this paper, we aim to explore the latter phenomenon by quantifying the causal effect of opening up trade across international land borders on the economic development of nearby regions.

The effect of trade on the economic development of border regions is of academic interest because theory can accommodate both scenarios, whereby trade either favors or impedes the economic catch-up of border regions. Trade-induced catch-up emerges most naturally from quantitative spatial models. However, when agglomeration forces are strong enough, trade liberalization can benefit interior regions disproportionately in a large class of models. Ours is the first study to investigate this question empirically across multiple countries, and our results suggest that, on the whole, trade liberalization disproportionately boosts border-region economies. In our baseline estimate, a 10% increase in exports to a particular neighbor country increases night lights by 2.8 percent at the border but only by 1.6 percent 300 kilometers inland.

Our analysis could interest policy makers. Border regions are relatively underdeveloped in countries across all levels of income. The stakes may be particularly high in developing countries, where unequal spatial development can generate tensions among local populations. Lack of development is then not just an economic problem but a political one as well: developing-country border areas are particularly prone to armed conflict (e.g. in Myanmar, Uganda, DR Congo, Nigeria, Colombia or Paraguay). In the most nefarious configuration, colonial-era borders divide ethnic homelands in low-income countries.[3] One might therefore think of our result as pointing to a hitherto unexplored 'non-traditional' gain from trade liberalization, of importance not only economically but also in broader political and societal terms.

We explore the effects of trade on border-region economic development across the entire globe, and thus face the challenge that economic activity is generally less precisely recorded at the sub-national than at the national level, especially in developing countries. As initially demonstrated by Henderson, Storeygard and Weil (2012), this measurement problem can be overcome by drawing on satellite night lights data. We

[1] See Table 2.

[2] On the endogenous formation of national borders, see Allen (2023).

[3] Michalopoulos and Papaioannou (2016) find that African ethnicities partitioned by a border are poorer and experience a significantly higher incidence of violence than non-partitioned ethnicities.

therefore test how cross-border trade affects light gradients with respect to distance from the border. An additional challenge for empirical analysis is that causation between changes in cross-border trade volumes and changes in border-region economic conditions could potentially run both ways. We therefore instrument bilateral exports with asymmetric changes in import tariffs on the opposite side of the border, with the aim of identifying plausibly causal effects running from trade to border-region economic development.

Our main results can be summarized as follows. Measuring night light intensity along cross-border road corridors over the 1995-2013 period worldwide, we detect a distinct border shadow, whereby average light intensity progressively decreases as one gets closer to the border. Most importantly, we show that trade liberalization, measured by the volume of exports between the two countries separated by a border, reduces the intensity of the border shadow. This effect is robust to the inclusion of small-scale location fixed effects, and it seems to be driven at least in part by local export-oriented production.

Our analysis speaks to substantial theoretical and empirical literatures.

Quantitative spatial models with rich underlying geographies have been used to explore within-country spatial effects of external trade liberalization (Allen and Arkolakis, 2014; Atkin and Donaldson, 2015; Cosar and Fajgelbaum, 2016; Fajgelbaum and Redding, 2022; Redding, 2016; Rossi-Hansberg, 2005).[4] In these models, market access typically is only one of several determinants of regional economic activity, combining with exogenously given features such as immobile factor endowments, productivity levels and/or amenities. Hence, even if better market access is associated with greater economic activity *ceteris paribus*, the disadvantages of border regions in terms of overall market access could be offset by advantages in terms of other locational determinants, thus making border shadows a likely but not necessarily pervasive phenomenon.[5]

We study this issue explicitly in Section 2, based on the spatial model of Allen and Arkolakis (2014). In that model, a border shadow can emerge for two distinct reasons. First, exogenously given features such as productivity or amenities can be different

[4]For a survey of this literature, see Redding and Rossi-Hansberg (2017). Earlier theoretical approaches included 'urban systems' models, featuring unique equilibria in perfectly competitive settings (e.g. Henderson, 1982; Rauch, 1991), and 'new economic geography' models featuring imperfectly competitive settings with multiple equilibria (e.g. Krugman and Livas Elizondo, 1996; Monfort and Nicolini, 2000).

[5]In Rossi-Hansberg (2005), for example, trade liberalization can change the sectoral specialization of border regions. Depending on the relative labor intensities of sectors, this may draw labor toward or away from the border region. Redding (2016, Section 5.5) simulates a hypothetical two-country world with a road running perpendicular to the border. Interestingly, he finds that the effect of trade liberalization on both population and real wages is positive at the point where the road crosses the border and then decreases monotonically along the road as one moves inland. Redding's (2016) analysis also illustrates how in general equilibrium border regions situated far from the border-crossing road could experience net losses in terms of population and/or wages, at the expense of border regions closer to the road.

close to the border. Second, a large border trade cost can substantially lower market access of locations close to the border. Using changes in the volume of bilateral trade as a proxy for changes in the border cost allows us to estimate the impact of border costs on the spatial distribution of economic activity. For large agglomeration or low congestion forces, a decrease in the border cost can actually exacerbate the border shadow. Our finding that the border shadow is on average reduced by trade indicates that agglomeration forces are not too strong, which we show to have implications for equilibrium stability in a larger class of models.

Our paper has a number of empirical antecedents. Following the seminal paper by Ades and Glaeser (1995), a number of cross-country studies have found trade openness to be associated with the spatial dispersion of activities within countries.[6] This is consistent with economic catch-up by border regions. Within-country studies, however, show more mixed results, partly because many of them focused on the case of Mexico, where maquiladora activity concentrated heavily in the northern part of the country, creating a second agglomeration pole which came to overtake the traditional one (Mexico city) in terms of manufacturing production (e.g. Hanson, 1998). A similar pattern has been observed in China, where rising trade openness has been associated with intensified concentration of industrial activity in the southeastern coastal region (Kanbur and Zhang, 2005).[7]

A later wave of empirical work used changes in national borders in 20th-century Europe as natural experiments. This allowed researchers to uncover plausibly causal evidence of the effect of cross-border market access on the economic fortunes of border regions. Cross-border liberalization was found to have had a significantly positive effect on the population growth of border regions in post-WWII Germany (Redding and Sturm, 2008). In a similar vein, Nagy (2022) has studied the effects of Hungary's shrunken territory and thus large-scale border changes post-WWI and found urbanization in counties close to the new border to have decreased significantly compared to counties in the country's interior. Brülhart, Carrère and Trionfetti (2012) and Brülhart, Carrère and Robert-Nicoud (2018) tracked the evolution of employment and wages in Austrian border regions after the opening of central and eastern European economies post-1989 – an event that initially was particularly close to a pure trade shock, as goods markets were opened up while labor mobility remained severely restricted. In the Cold War years, population density, employment density and wages within Austria were progressively lower as one got closer to the Iron Curtain. After the fall of the Iron Curtain, however, both employment and wage growth was stronger in locations close to the old Iron Curtain, consistent with cross-border

[6] Ten out of eleven cross-country analyses surveyed by Brülhart (2011) documented trade-related spatial dispersion.

[7] In this paper, we focus on land borders. Among other issues, it is impossible to define "neighbor countries" in the case of sea borders.

trade liberalization disproportionately favoring the economic development of border regions.

In this paper we offer three main extensions to this existing body of empirical research. First, we extend the analysis to the entire world economy.[8] Second, we seek to quantify effects that were mostly captured only in qualitative terms in the existing quasi-experimental work. By taking measured changes in trade intensities as our explanatory variable instead of the binary before-after analyses of the Iron Curtain studies, we can compute magnitudes of border-region responses with respect to measurable magnitudes of changes in trade openness. Third, we seek to distinguish effects at the border, gradients as one moves away from border crossing points along main roads, and gradients as one moves away from the border and from the roads.

The remainder of the paper is organized as follows. Section 2 provides theoretical background, Section 3 describes the data, Section 4 discusses estimation issues, Section 5 presents our main empirical results, Section 6 presents three empirical extensions, and Section 7 concludes.

2 Theory

To motivate our empirical strategy and interpretation of the results, we start with a spatial model similar to that of Allen and Arkolakis (2014). We briefly describe it here and relegate the details to Appendix A. The world is composed of N locations, each of them producing a differentiated good. There is a continuum of agents, who get utility from an Armington CES aggregate over goods produced in every location, with elasticity of substitution σ.[9]

A location i's productivity is given by $A_i = \bar{A}_i L_i^{\alpha}$ where $\bar{A}_i$ is an exogenous productivity, L_i is the population in i, and α is a scale economy parameter. In location i, an agent gets an indirect utility $u_i = \bar{u}_i L_i^{\beta} \frac{w_i}{P_i}$, where $\bar{u}_i$ is an exogenous amenity term, β is a congestion elasticity (if $\beta < 0$), w_i is the wage in region i, and P_i is the price index corresponding to the CES utility function ($P_i^{1-\sigma} = \sum_j p_{ji}^{1-\sigma}$, where p_{ji} is the price of location j's good in location i). Agents are free to move, hence welfare is equalized across space. Trade is balanced, so that total output is equal to total expenditure: $w_i L_i = \sum_j X_{ji}$ where X_{ji} are exports from j to i.

The price of location j's good in region i is given by $p_{ji} = p_j \tau_{ji}$ where τ_{ji} is an iceberg trade cost. We assume that the trade cost only depends on distance, as well as a potential border cost if the two locations are in different countries. Under

[8] Hirte, Lessmann and Seidel (2020) also use night-lights data to study the effect of international trade on within-country regional inequality with world-wide country coverage. Their analysis focuses on indices of within-country regional inequality without considering border regions specifically.

[9] This model is isomorphic to a large class of spatial models, so that our findings apply to many settings (see Allen, Arkolakis and Takahashi 2020).

symmetric trade cost and balanced trade, it can be shown that $P_i^{1-\sigma} = \sum_j \tau_{ij} \frac{Y_j}{P_j^{1-\sigma}}$ (Donaldson and Hornbeck, 2016).

In equilibrium, output in region i will be given by:

$$\gamma_1 \ln Y_i = C_w + C_L + (1-\beta) \ln \bar{A}_i^{\sigma-1} + (1+\alpha) \ln \bar{u}_i^{\sigma-1} + (2+\alpha-\beta) \ln P_i^{1-\sigma}, \quad (1)$$

where $\gamma_1 = 1 - \alpha(\sigma - 1) - \beta\sigma$ and C_w and C_L are normalization constants coming from a numeraire normalization as well as welfare equalization across space.[10] It is apparent from equation (1) that if $\gamma_1 > 0$, output might be lower close to the border if the exogenous productivities $\bar{A}_i$ and amenities $\bar{u}_i$ are low, or if the measure of market access $P_i^{1-\sigma}$ is low because of the border cost. To link $P_i^{1-\sigma}$ to observables in the data, we consider changes in output. Assuming no changes in exogenous productivity and amenities (for example following changes in trade costs), the change in output can be rewritten as:

$$\gamma_1 \Delta \ln Y_i = \Delta C_w + \Delta C_L + (2+\alpha-\beta)\, \Delta \ln P_i^{1-\sigma}. \quad (2)$$

Hence, variation in the change of output across locations will be captured by the change in their price index.

To link this model to an estimable equation relevant to the border shadow, we now assume that locations are divided into two countries, separated by a border. The trade costs between region i and j located in different countries is given by $\tau_{ij} = \exp\left(\beta d_i^{border} + b + \beta d_j^{border}\right)$ where d_i^{border} is the distance from location i to the border, and b is a border crossing cost (e.g. a tariff).

Under these assumption, it can be shown that for a location i located in country 1, the change in price index due to a change in the border cost is given by:

$$\frac{\partial \ln P_i^{1-\sigma}}{\partial b} = \underbrace{(1-\sigma)\,\frac{X_{i,C_2}}{Y_i}}_{(1-\sigma)\times\text{export share}} + \frac{\gamma_2}{\gamma_1} \sum_j \frac{X_{ij}}{Y_i} \frac{\partial \ln P_j^{1-\sigma}}{\partial b}, \quad (3)$$

where X_{i,C_2} are the total flows from i to locations in country 2 and $\gamma_2 = 1 - \beta + \alpha\sigma + \beta\sigma$ and $\frac{X_{i,C_2}}{Y_i}$ is the share of exports to C_2 in i's total output. Appendix A shows that this share captures all the first order variation in the price index and is negatively correlated with i's distance to the border under regularity conditions. Going back to equation (2), we find:

$$\gamma_1 \Delta \ln Y_i \approx \Delta C_w + \Delta C_L + (2+\alpha-\beta) \underbrace{\frac{\partial \ln P_i^{1-\sigma}}{\partial b}}_{\text{proxy with } (1-\sigma) d_i^{border}} \Delta b. \quad (4)$$

[10] Appendix A shows a similar expression when labor is only mobile within a country and not across borders. In that case, C_L will be country specific.

To get to an estimating equation, we can further proxy the change in the border cost by the change in total exports between the two countries, to obtain:

$$\begin{aligned}\gamma_1 \ln Y_{it} \quad \approx \quad & \underbrace{C_{wt} + C_{Lt}}_{\text{country-time FE}} + \underbrace{(1-\beta)\ln \bar{A}_i^{\sigma-1} + (1+\alpha)\ln \bar{u}_i^{\sigma-1} + (2+\alpha-\beta)\ln P_{i0}^{1-\sigma}}_{\text{location FE}} \\ & + (2+\alpha-\beta)(1-\sigma) \quad \underbrace{\frac{\partial \ln P_{i0}}{\partial b}}_{\text{proxy with } d_i^{border}} \quad \underbrace{\Delta b_t}_{\text{proxy with } \ln X_{C_1C_2}}\end{aligned} \tag{5}$$

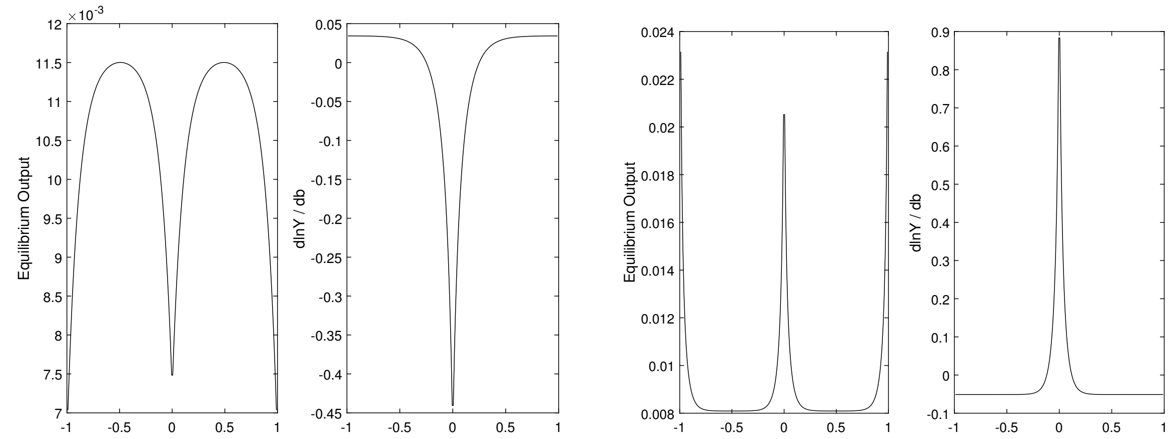
Hence, we can regress the output of location i at time t on a country-time fixed effect, on a location fixed effect, and on exports interacted with the distance to the border – our exact empirical specification (see equation 7 below).

The sign of the coefficient on the interaction term is informative on the sign of the structural composite of parameters $\frac{(2+\alpha-\beta)(1-\sigma)}{\gamma_1}$. An increase in total exports (proxying for a decrease in the border cost, $\Delta b_t < 0$) should decrease relative output in locations further away from the border if $\frac{(2+\alpha-\beta)(1-\sigma)}{\gamma_1} < 0$. Since $1-\sigma$ is the trade elasticity, we know that $1-\sigma < 0$. Further, β represents the elasticity of utility with respect to population and is typically negative, so that it is most likely true that $2+\alpha-\beta > 0$. Hence, the sign of the coefficient is informative on the sign of $\gamma_1 = 1-\alpha(\sigma-1)-\beta\sigma$.

This combination of parameters turns out to be important in determining the uniqueness and stability of equilibria in this class of spatial models. Indeed, Allen and Arkolakis (2014) show that if $\gamma_1 > 0$, all equilibria are regular (Theorem 2) and point-wise locally stable (Proposition 1). Furthermore, if $|\gamma_2/\gamma_1| < 1$ (which implies $\gamma_1 > 0$), the equilibrium is unique. Intuitively, $\gamma_1 > 0$ guarantees that scale economies (α and β) are not strong enough relative to congestion forces to create multiple or unstable equilibria. As a result, a positive coefficient on the interaction term would reject the hypothesis that $\gamma_1 > 0$. While a negative coefficient (which is what we find empirically) does not prove the alternative hypothesis ($\gamma_1 > 0$), it is still reassuring for the properties of equilibria in this class of models.

Figure 1 illustrates the change in the border "shadow" in a simplified line economy - a similar exercise as in Allen and Arkolakis (2014) and Redding (2016) - where each location is a dot on the line between -1 and 1, and there is a border cost at 0. There is a unit mass of population in each country, fully mobile within the country but not across the border. Each location is identical and differs only through its position on the line. The left panel (a) displays a case where $\gamma_1 > 0$ (using the baseline parameter values from Allen and Arkolakis, 2014). In this case, equilibrium output shown on the left figure is lower closer to the border, and the elasticity of output with respect to the border cost shown on the right figure is more negative for locations close to the border – consistent with a border shadow that is exacerbated by high trade costs. The

Figure 1: Spatial equilibrium and border effect on a line



(a) $\alpha = 0.1$, $\beta = -0.3$, $\sigma = 9$, $\gamma_1 > 0$ (b) $\alpha = 0.3$, $\beta = -0.1$, $\sigma = 9$, $\gamma_1 < 0$

Note: The figure displays the equilibrium output on the line economy, for different parameter values. In each panel, the left side displays the spatial distribution of output. The right side displays the elasticity of output with respect to the border cost. When $\gamma_1 > 0$, the elasticity is consistent with a border shadow. When $\gamma_1 < 0$, the elasticity is instead positive closer to the border. In this particular case, there is no border shadow even in levels with $\gamma_1 < 0$, but this need not be the case for other amenities or productivity combinations.

right panel (b) displays a case where $\gamma_1 < 0$. In this case, the equilibrium population is concentrated at the edges, and the elasticity of border cost is now positive closer to the border.[11] In this particular case, there is no border shadow even in levels with $\gamma_1 < 0$, but this need not be the case for other amenities or productivity combinations as we show in Appendix A.

To summarize, the theoretical predictions are ambiguous: trade liberalization might reduce the border shadow under some parameter values, but it might exacerbate it when scale economies are large. Thus, we turn to the data to study the question empirically.

3 Data

3.1 Construction of the dataset

The uses and limitations of *night lights* data as a proxy for economic activity have been widely discussed.[12] Bruederle and Hodler (2018), for instance, document how night lights correlate positively and monotonically with a range of gridded development indicators. Levin *et al.* (2020) show that the raw correlation between night lights and country-level GDP is positive but somewhat noisy, a parabolic regression

[11] Note that in this case, the equilibrium is not point-wise locally stable. Nevertheless, the model produces a counterintuitive flattening of the border shadow as the border cost increases.

[12] See e.g. Sutton, Elvidge and Ghosh (2007); Henderson, Storeygard and Weil (2012); Donaldson and Storeygard (2016); Pinkovskiy and Sala-i-Martin (2016).

of one on the other yielding an R-squared of 0.5. They point out that between-country comparisons of night lights are complicated by differences in surface reflection due to different topography and land cover (albedo), gas and oil resources and lighting standards. Within countries, however, they document that the evolution in night lights over time tracks known economically relevant events with remarkable accuracy.[13] By way of an additional validation exercise, we have correlated published GDP data for EU NUTSIII regions with night lights for those same regions in the five sample years of our main analysis, and found the correlation to be highly significant not only in the cross section but also in the time-series ('within') dimension.[14] Given that all our estimations exploit variations over time in night lights, conditional on country-year effects, night lights should offer a reliable measure of changing levels of economic activity. Finally, if night lights were a proxy for population rather than for local-level GDP or GDP per capita, Appendix A shows that the predicted border gradient would have the same sign within the Allen-Arkolakis (2014) framework.

We use data on night lights from the Earth Observation Group (see Appendix B for details). Radiance is quantified on a bounded scale ranging from zero to 63. Raw light values are intercalibrated between years, to account for the fact that different satellites were used over time.

Our analysis focuses on locations within 300 kilometers of international land borders. Distance from the border is measured along *road corridors*.[15] We consider all border-crossing roads according to the 2011 version of the ESRI World Roads dataset (see Figure 2).[16] Our analysis is thus based on 1,799 border crossings. As shown in Table 1, we observe 25 land border crossings in the average advanced economy but only 18 in the average developing country, reflecting the lower density of the road network in the latter group. Given the larger number of developing countries, they nonetheless account for some 64% of border crossings observed in our data.

Based on our sample of border-crossing roads, we perform a number of operations on the raw lights data using GIS software. An illustration is given in Figure 3. Panel (a) shows the raw data of our sample roads in the case of the border region between Sudan, Eritrea and Ethiopia. To be part of our analysis, a road needs to cross a land border and be classified as a "highway", "major road" or "local road" in the ESRI dataset. The figure illustrates how lights cluster along such road corridors. Panel (a)

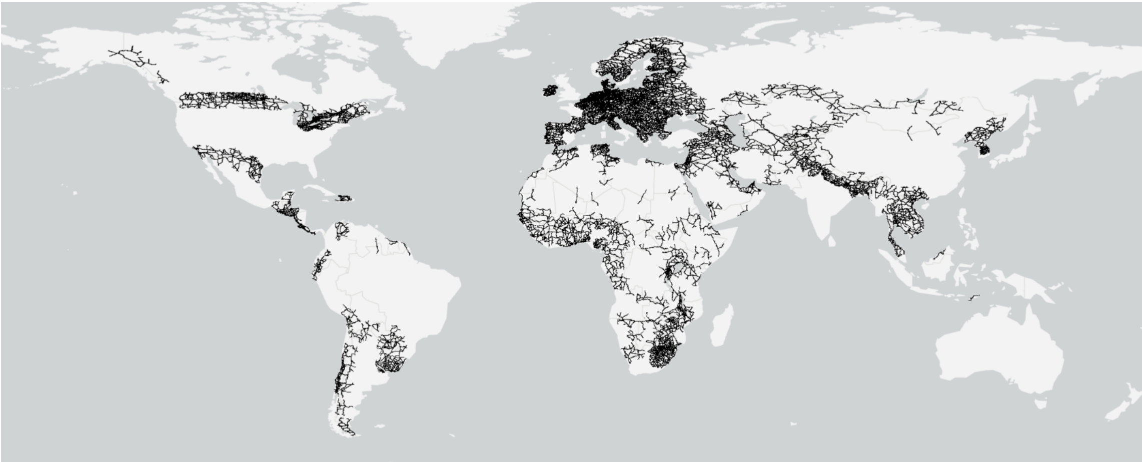
[13]See Figure 20 in Levin *et al.* (2020), where they show how night lights e.g. track the impact of war destruction in Syria, of the economic boom in Dubai and of economic decline in Venezuela.

[14]See Appendix Table A1.

[15]Road corridors are defined by border crossing points. All cells that share a certain border crossing as their closest point of accessing neighbor country c' are assigned to the same road corridor. One can think of this as a tree rooted at a particular border crossing, such that all cells can be assigned to the closest root in terms of network distance.

[16]The identification of roads is based on information provided by national authorities. Since our estimations exploit only within-country variation, any definitional differences across countries will not affect our analysis.

Figure 2: Cross-border roads



Note: Major cross-border roads up to 300km from the border, as defined in the 2011 ESRI World Roads dataset.

Table 1: Borders and border crossings

	Land borders per country	Border crossings per country	Border crossings per border	Total number of border crossings	Total number of grid cells
Advanced economies (40)	3.53	24.75	7.02	653	170,219
Developing economies (114)	3.90	17.54	4.49	1,146	429,090

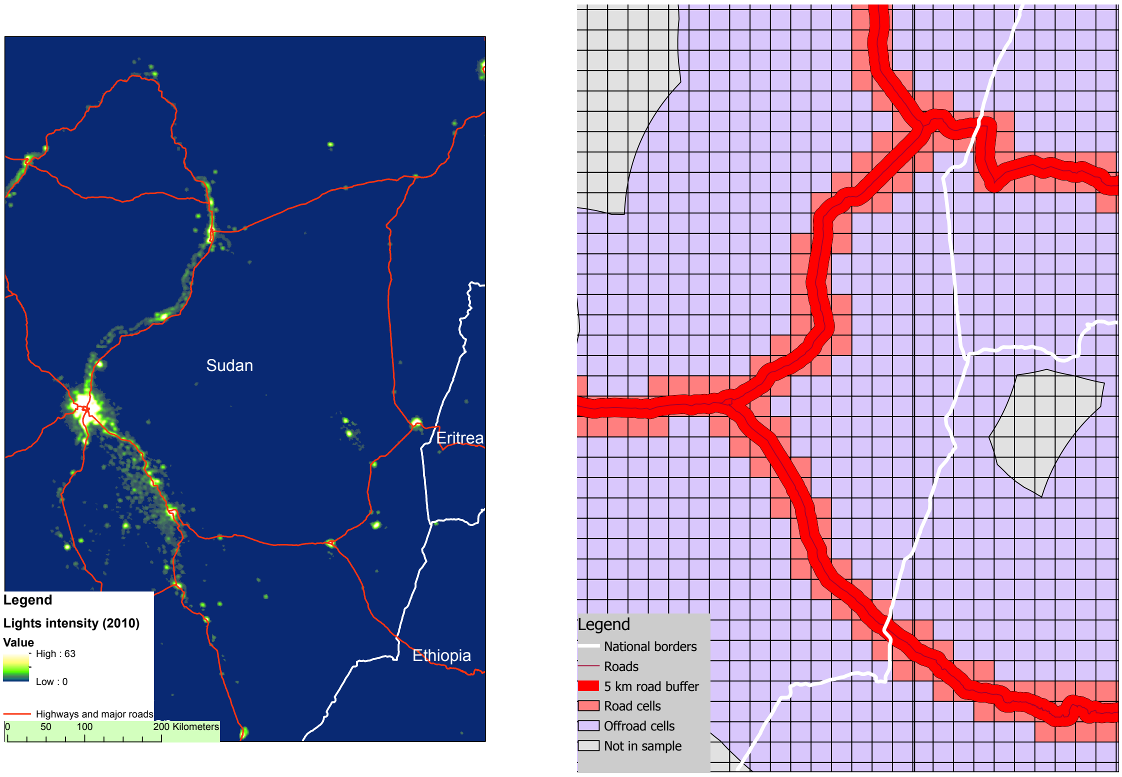
Note: Countries grouped according to the 2015 World Bank classification.

also offers an example of the border shadow: light intensity diminishes gradually as one moves away from the Sudanese capital Khartoum toward the Ethiopian border.

Figure 3: Roads, lights and grid cells

(a) Roads and lights

(b) Units of observation

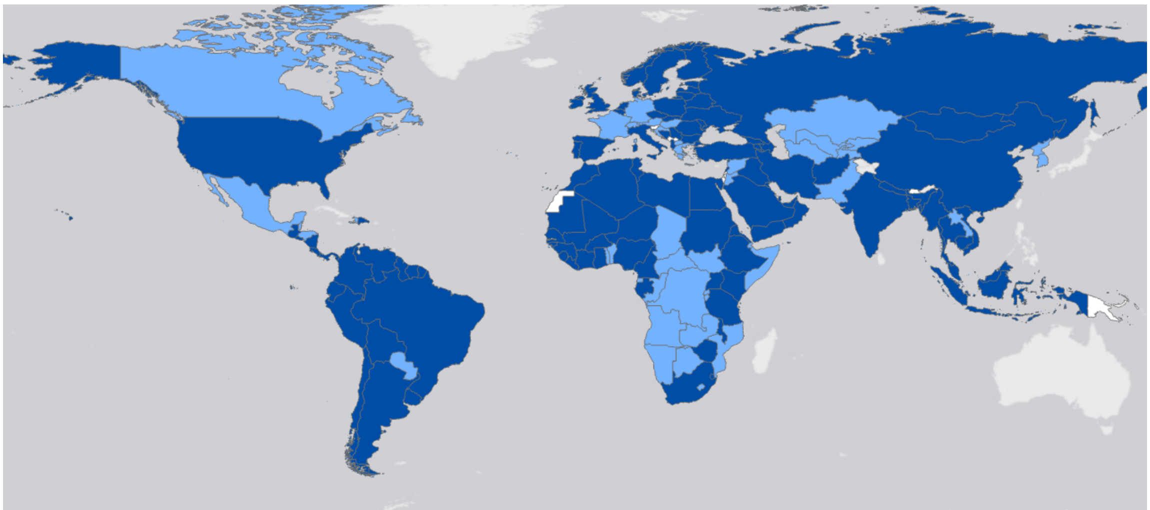


Note: National borders in white, major roads in red. Grid cells illustrated in panel (b) enter the baseline sample (on-road + off-road) if their road distance from the closest border is $<= 300$ kilometers and their geodesic distance from the closest road is $<= 100$ kilometers. Source: ESRI ArcGIS.

In panel (b) of Figure 3, we zoom in further to illustrate the construction of our units of observation. Our basic units are 10 $\times$ 10 kilometer grid cells. In order to be part of our sample, a grid cell needs to be within 300 kilometers along the road from the border. Within each of these cells, we compute the average light intensity of all 1 $\times$ 1 kilometer light pixels contained by the grid cell. We then construct buffers of five kilometers on either side of the border-crossing roads. We also consider additional outer buffers with a width of up to 100 kilometers on either side of road corridors. This allows us to distinguish between cells that are located directly on a road (on-road cells) and cells located in border regions but away from the main roads (off-road cells). By doing this, we obtain some 227,000 on-road and 372,000 off-road grid cells for each of the years 1995, 2000, 2005, 2010 and 2013.[17] For every on-road cell, we

[17]The DMSP satellites were discontinued in 2013 and replaced by a new system of satellites called VIIRS. As there is no consensus on how to convert values from different satellites to a unified scale (see, e.g., Chen and Nordhaus, 2015), we limit our baseline panel to the period from 1995 to 2013.

Figure 4: Dark land border regions dominate



Note: Sample countries are displayed according to the average light intensities in border regions in relation to the respective country average before conditioning on any covariates. In dark blue countries, border regions, defined as within up to 50 kilometers, are on average darker than interior and coastal regions, and vice-versa for light blue countries.

compute the distance of its center from the closest border along the border-crossing road. For every off-road cell, we compute the distance from the closest on-road cell as well as the distance from the border along the road from that on-road cell.[18]

Detailed information on all our data sources and definitions is provided in Appendix B.

3.2 The border shadow

Before analyzing lights within border regions, we provide some context on the development of border regions as measured through light intensity compared to non-border regions. To do so, we compute average light intensities within countries separately for grid cells located within 50 kilometers of land borders (the "border region") and for grid cells located further inland.[19] The results are shown in Figure 4, where all countries featuring border regions that are relatively darker than the respective interior regions are colored in dark blue. In the raw data border regions have lower light intensities than interior regions in most but not all countries: 70% of mapped countries feature relatively "dark" border regions (100 of the 143 countries shown in Figure 4). Weighted by population, these account for 83% of the sample, and weighted by GDP, they account for 85% of the sample.

As shown in Table 2, border-region road corridors are on average some 18% darker

[18]Summary statistics for all variables are given in Appendix Tables A2 (all observations), A3 (on-road observations only) and A4 (off-road observations only).

[19]Countries that are too small to host an interior region according to this definition are dropped.

Table 2: Average light intensity along cross-border road corridors

	Mean	Std. dev.	t stat.	No. obs.
Border region (0-50 km from border)	4.95	5.46		143
Interior region (50-300 km from border)	6.00	6.51		143
Difference	1.05		4.04	

Note: Scale of light intensity: 0–63; country-level averages.

within the first 50 kilometers from the border than in the 50-300 kilometer range. This difference is statistically significant.

The location of borders, of course, is not random and often coincides with inhospitable terrain: borders typically cross "naturally dark" regions. Part of the observed gradient is therefore undoubtedly explained by the endogeneity of border locations and not reflective of any policy-driven barriers to trade. In the following, we seek to isolate the spatial effects of man-made borders.

4 Estimation

Our main aim in this paper is to study the effect of trade liberalization between neighboring countries on light gradients around the border. Starting from a situation with a border shadow, theory suggests two possible scenarios. If the productivity advantages of interior regions outweigh their disadvantages from greater distance from the border, then the interior of the country will benefit more from the liberalization than the border region, thus steepening the lights gradient for strong enough agglomeration forces. Conversely, trade liberalization might flatten the lights gradient and therefore brighten up the border shadow. As shown in Section 2, a standard quantitative spatial model can accommodate both configurations.

Note that our two stylized scenarios assume positive effects of trade liberalization on local light intensity at all locations. When, as in most of our empirical specifications, 'trade' stands for exports, this assumption is consistent with all theoretical models and evidence we are aware of. However, when 'trade' is understood to mean imports, then negative regional effects could be possible.[20] We shall therefore explore the import channel as well, and our empirical specifications naturally allow for the possibility of negative average trade effects on light intensity at any border-distance interval.

[20]For evidence on potentially long-lasting negative impacts of import liberalization on particularly affected local labor markets see, e.g., Autor, Dorn and Hanson (2013), Dix-Carneiro and Kovak (2017) or Caliendo, Dvorkin and Parro (2019).

4.1 Empirical model

Our empirical strategy consists of estimating changes in night-light distance gradients as a function of changes in bilateral exports. Let $Y_{irscc't} = Y_{it}$ be the light intensity of grid cell i located on border-crossing road r in sub-national region s leading from country c to country c' in year t. In order not to lose grid cells with zero measured lights through the log transformation $y_{it} = \ln(Y_{it})$, we (a) add 1 to recorded lights before taking logs, we (b) estimate Poisson models on lights measured in levels, and we (c) estimate linear specifications with lights measured in levels.[21] Roads r are defined as belonging to one country only, such that every cross-border corridor consists of two "roads". Subscripts c, s, r and c' are implied by i, as every cell is uniquely assigned to a country, region, nearest road and neighbor country. We denote by d_i^{border} grid cell i's distance from the nearest border crossing along road r. $T_{cc't}$ stands for the log value of trade of country c with neighboring country c' across that border (along road r or some other road that crosses the cc' border), where trade is measured alternatively as exports from c to c' (our baseline) or as imports by c from c'.

Our baseline empirical model can be written as follows:

$$y_{it} = \ln(Y_{it}) = \beta_0 + \beta_1(d_i^{border} \times T_{cc't}) + \gamma_i + \gamma'_{cc't} + u_{it} \quad (6)$$

where γ_i denotes 10×10 kilometer grid-cell fixed effects that soak up all cross sectional variation, thus reducing identifying variation entirely to changes over time. In addition, we control for country-pair-year fixed effects $\gamma'_{cc't}$. Our main parameter of interest β_1 can nontetheless be estimated, as the interaction term varies across cells within each country-pair-year $cc't$. The estimate of β_1 allows us to gauge how increased trade changes the distance gradient.

We estimate this model alternatively for on-road locations (red grid cells in Figure 3b), for off-road locations (blue grid cells in Figure 3b), and for both sub-samples combined. All off-road grid cells are uniquely attributed to a nearest on-road grid cell in terms of geodesic distance, and d_i^{border} is measured along that road.

In a somewhat less demanding specification, we also estimate the following model:

$$y_{it} = \ln(Y_{it}) = \beta_0 + \beta_1(d_i^{border} \times T_{cc't}) + \beta_2 T_{cc't} + \gamma_i + \gamma_{ct} + u_{it}, \quad (7)$$

where we control for country-year fixed effects γ_{ct} to filter out country-level changes in luminosity.[22] This specification also allows us to estimate β_2, the effect on night lights of increased cross-border trade at the border crossing (where $d_i^{border} = 0$).

[21] In order not to overcrowd the tables, estimates based on the latter specifications are relegated to the Appendix.

[22] Pinkovskiy (2017) shows that night lights exhibit significant nation-specific variation.

4.2 Identification and inference

When seeking to capture the causal effect of changed trade intensities, we need to address the potential endogeneity of trade. Not only can trade be expected to affect activity as measured through lights, but changes in domestic economic activity can in turn affect the volume of cross-border trade.

Arguably, grid cell, country-year and country-pair-year fixed effects mitigate much of this concern. Nonetheless, we also estimate equations (6) and (7) by instrumenting bilateral exports $T_{cc't}$ with asymmetric tariff changes of destination country c' on goods from origin country c. Since trade weights could be endogenous, tariffs are computed as unweighted averages across sectors. We analogously instrument the interaction term $(d_i^{border} \times T_{cc't})$ with the product of distance and asymmetric neighbor-country tariff changes.

We define a change in the statutory tariff of country c' on exports from country c as 'asymmetric' if it meets one of the following three conditions:

- The change in tariffs is unilateral, meaning that c' changed its tariff on goods from country c but country c did not change its tariff.
- Both countries changed their tariffs but in opposite directions.
- The two countries changed their tariffs in the same direction, but the percentage-point change adopted by the importing country c' is at least twice the size of that adopted by the exporting country c.

By applying this restriction, we exclude tariff changes that are very similar on both sides of the border and are thus more likely to result from a common agreement to lower tariffs. This restriction reduces our sample from 1,799 to 1,001 border crossings and from 599,309 to 292,701 grid cells. We show in Appendix Table A7 that the change in the estimation sample does not qualitatively affect our findings.

Our identifying assumption is that activity in grid cell i of country c does not directly affect asymmetric tariff changes made by neighbor country c'. Given the small size of our cells and the inclusion of country-year fixed effects, this assumption strikes us as unproblematic. The exclusion restriction we impose requires that, conditional on fixed effects, asymmetric tariff changes by country c' affect economic activity in country c only through the volume of exports from c to c'. We consider this to be an equally plausible assumption, because it is difficult to conceive of another causal channel through which activity at a particular location could be affected by changes in tariffs of another country. Tariff revenue, for instance, is unlikely to be spent in regions outside of the country applying the tariff. We systematically report Kleibergen-Paap (K-P) first-stage F-statistics for the joint significance of both instruments and Sanderson-Windmeijer (S-W) F-statistics for individual endogenous variables.[23]

[23] The limitation of K-P F-statistics in our context is that no critical values exist for the case of

Throughout the analysis, we cluster standard errors two ways, by grid cell i and by region-year st. In a robustness test, we also cluster by country-year ct. Clustering by region-year should account for regional economic co-evolutions. Clustering by country-year in addition accounts for nation-level co-evolutions, but may well be overly restrictive.

5 Results

5.1 Baseline estimates: How exports affect light gradients

Table 3 presents our baseline estimates. Panel A shows estimates based on on-road grid cells (equations 6 and 7), Panel B shows corresponding estimates for off-road grid cells, and Panel C shows estimates for both sub-samples combined. For all three samples, we estimate linear specifications with the dependent variable in logs, without and with instrumenting exports, and with a Poisson estimator.[24]

Columns (1) to (4) contain results for specifications featuring grid-cell fixed effects, which we always include, and country-pair-year fixed effects, which allow us to estimate only the coefficient on the interaction of bilateral exports and distance from the border, our effect of main interest (see equation 6). Columns (5) to (8) show corresponding results for specifications according to equation (7).

Our coefficient estimates $\hat{\beta}_1$ on the interaction term turn out to be stable across specifications, and statistically significant throughout.[25] The estimated coefficents are negative, consistent with border light gradients being attenuated when exports grow. For example, the estimated coefficient in the on-road sample of Table 3, column (2), implies that the brightening effect of export growth falls by some 2.9 percent with every 100 kilometers of distance from the border.

If we impose a less demanding fixed-effects structure, using specification (7), we can also identify the main effect of export growth, $\hat{\beta}_2$ (columns 5-8 of Table 3). This coefficient turns out to be positive and statistically significant throughtout, confirming that bilateral export growth is associated with increased lights at the relevant land border. Instrumenting generally increases the estimated main effects $\hat{\beta}_2$ in (columns 6 and 8 of Table 3). This could reflect measurement error on trade volumes biasing our

multiple instruments with potentially heteroskedastic errors (Andrews *et al.*, 2019). The limitation of the SW F-statistic is that it is not designed for the case of heteroskedastic errors. We follow current practice of reporting both measures.

[24] For OLS and IV regressions, we use respectively the Stata commands *reghdfe* and *ivreghdfe* by Correia (2017) and Correia *et al.* (2019). For Poisson regressions, we use the *ppmlhdfe* command by Correia *et al.* (2020). For the Poisson estimation, we follow the control function approach of Lin and Wooldridge (2019) and label it "Poisson IV".

[25] When instrumenting (column 2), the first-stage F statistics are above conventional acceptance thresholds. In Appendix Table A8, we report corresponding first-stage estimates, regressing bilateral exports on asymmetric tariff changes, revealing a negative relationship between tariffs and exports as expected.

Table 3: Baseline estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:								
Light intensity by grid cell and year (Y_{it})	Logs: $ln(Y_{it}+1)$		Levels: Y_{it}		Logs: $ln(Y_{it}+1)$		Levels: Y_{it}	
	OLS	IV	Poisson	Poisson IV	OLS	IV	Poisson	Poisson IV
Panel A: On-road grid cells only								
Bilateral exports (in logs)					0.051***	0.282**	0.083***	0.088**
					(0.011)	(0.135)	(0.025)	(0.037)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.017***	-0.029**	-0.015***	-0.016**	-0.015***	-0.040***	-0.014***	-0.015*
	(0.003)	(0.012)	(0.005)	(0.007)	(0.003)	(0.014)	(0.005)	(0.008)
K-P F statistic		65.32				5.90		
S-W F statistic (main effect)						23.16		
S-W F statistic (interaction)		65.32				82.84		
# Clusters	3,635	3,635	3,635	3,635	3,635	3,635	3,635	3,635
# Observations	355,664	355,664	355,664	355,664	355,664	355,664	355,664	355,664
Panel B: Off-road grid cells only								
Bilateral exports (in logs)					0.020***	0.055*	0.104***	0.112***
					(0.004)	(0.030)	(0.022)	(0.031)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.008***	-0.015**	-0.037***	-0.037***	-0.007***	-0.015**	-0.031***	-0.032***
	(0.001)	(0.007)	(0.007)	(0.009)	(0.001)	(0.006)	(0.007)	(0.010)
K-P F statistic		54.82				5.53		
S-W F statistic (main effect)						89.43		
S-W F statistic (interaction)		54.82				57.03		
# Clusters	3,455	3,455	3,453	3,453	3,456	3,456	3,454	3,454
# Observations	581,945	581,945	581,663	581,663	581,948	581,948	581,666	581,666
Panel C: On-road + off-road grid cells								
Bilateral exports (in logs)					0.031***	0.113**	0.092***	0.094***
					(0.006)	(0.053)	(0.022)	(0.032)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.013***	-0.024**	-0.027***	-0.027***	-0.011***	-0.026***	-0.024***	-0.024***
	(0.002)	(0.010)	(0.006)	(0.008)	(0.002)	(0.010)	(0.006)	(0.008)
K-P F statistic		66.34				5.70		
S-W F statistic (main effect)						65.39		
S-W F statistic (interaction)		66.34				70.39		
# Clusters	3,872	3,872	3,871	3,871	3,873	3,873	3,872	3,872
# Observations	937,609	937,609	937,607	937,607	937,612	937,612	937,610	937,610
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

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

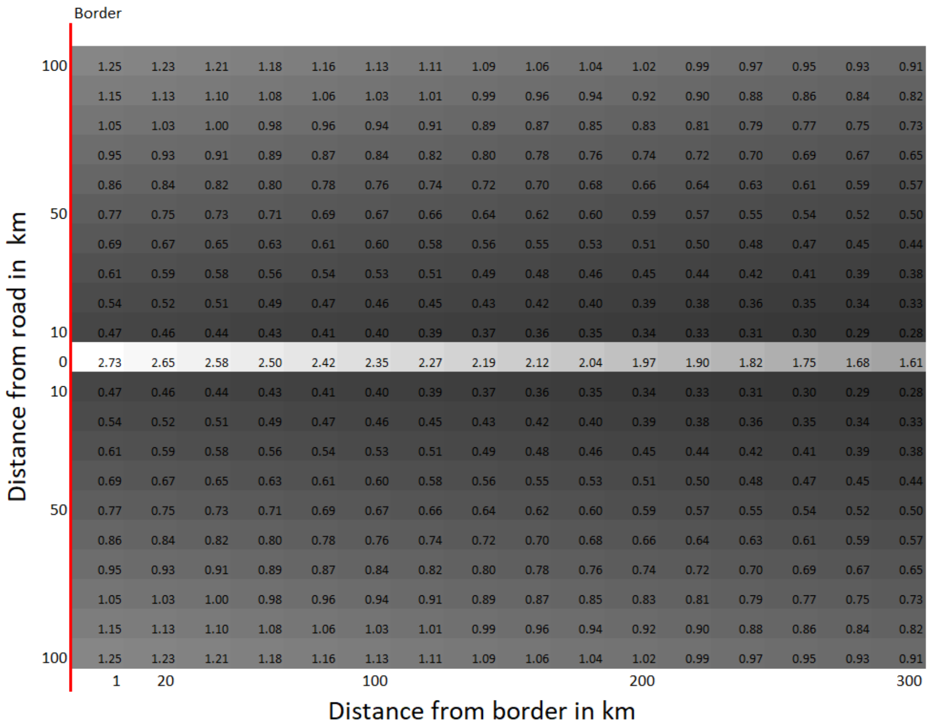
Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

estimates towards zero in the OLS estimations.[26] We turn to discussing the implied magnitudes below.

Our estimates based on off-road cells are qualitatively similar to those based on on-road cells. This suggests that we are not merely picking up lights emitted by increased traffic along cross-border corridors. Our on-road estimates that include the main effect of trade imply that a 10% increase of cross-border trade will increase night lights by some 2.8% percent at the border crossing but only by 1.6% 300 kilometers inland (Panel A, column 6 of Table 3). We illustrate this in Figure 5. The graph shows changes in border-region night lights implied by a model that is equivalent to

[26] One issue with the results in column (6) is that first-stage F statistics in specifications with country-year fixed effects are somewhat below conventional acceptance thresholds, ranging between 5.5 and 5.9. As we show below, this is likely due in part by noisy measurement of export flows and applied tariffs, especially in developing countries, where a substantial share of trade is informal. When we focus on advanced economies only, our tariff instrument turns out to be strong also in specifications with country-year fixed effects only (see Section 5.3.1 below).

Figure 5: Predicted percentage change in light intensity associated with a 10% increase in exports



Note: The graph shows predicted percentage changes in light intensity after a 10% increase of exports starting from a scenario with trade set to the mean value in our data, based on separate regressions for on-road and off-road grid cells, with grid cell and country-year fixed effects, and exports instrumented with asymmetric tariff changes. Darker colors symbolize lower light growth.

column (6) of Table 3, based on separate regressions for on-road and off-road grid cells. We draw a hypothetical 300×200 kilometer area with an international border at its western edge and a perpendicular border-crossing road running through its middle. In this grid, we report predicted percentage changes in light intensities for a 10% increase in exports, starting from the mean value. Variation across grid cells in lights growth is determined by the estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ of equation (7).[27] The shading of the grid cells illustrates predicted changes in light intensities, and predicted values are reported inside each cell. It appears clearly in Figure 5 that our estimates imply exports to brighten up locations close to the border more strongly than locations further inland, and that this is true both along and off the main border-crossing roads. Exports are found to bring about the strongest growth in lights on the main road corridors.[28]

[27] We retain estimated values of all these parameters, including coefficients that are not statistically significantly different from zero, as the point estimates remain the values with the highest likelihood even in those instances.

[28] In Appendix Figure A1 we illustrate the same effects but in terms of absolute changes in predicted lights. It emerges clearly that the absolute brightening effect predicted by our regression estimates is more than an order of magnitude larger on cross-border road corridors than at locations further removed from those roads. The slight positive gradient of light changes with respect to distance to the

In summary, we find increased trade to attract activity towards border regions, both on and off border-crossing road corridors. Our estimates also imply that, within our sample distance band of 300 kilometers, exports are associated with increases in lights for all grid cells including those furthest removed from the border and the main road.[29]

5.2 Robustness

We explore the robustness of our baseline estimates in six different ways.

First, we investigate the sensitivity of our results to the choice of distance cut-off, which we set at 300km for the baseline estimations. Looking at various cut-offs starting at 150km, we find that our estimates remain qualitatively unchanged.[30]

Second, we drop grid cells located on border crossing points, since our effects might to some extent be driven 'mechanically' by greater activity at customs posts. It turns out that any such effects are barely discernible.[31]

Third, we drop small countries from the estimation sample, as they do not have an 'interior' region beyond our distance cut-off. Again, our baseline estimates remain essentially unchanged.[32]

Fourth, we apply country-year level error clustering instead of our baseline region-year level clustering. This reduces the number of clusters by an order of magnitude, but our estimated interaction effects remain statistically significant.[33]

Fifth, we investigate our IV strategy. Reduced-form estimates yield the expected results: higher asymmetric tariffs are associated with lower night lights at the border and significantly more positive gradients with respect to distance from the border.[34]

Sixth, we replace our instrument based on asymmetric tariff changes by an instrument borrowed from Egger *et al.* (2019), defined as the interaction between annual global oil prices and the bilateral road distance separating the closest cities with a population of at least 500,000 on either side of the border. This instrument is not bi-directional, unlike our main asymmetric tariff instrument. Nonetheless, our qualitative results turn out to be robust.[35]

Finally, we define trade $T_{cc't}$ not as exports but as imports. Specifically, we con-

road is not statistically significant.

[29]Grid cells that are further than 100 kilometers away from a major border-crossing road are found only in areas with very low population density, typically in large developing countries. As the satellites mostly do not record any measurable light emissions in these areas, it would be mechanically impossible to find a decrease in light intensity in those cells. Hence our chosen buffer width of 100 kilometers on either side of the road.

[30]See Appendix Table A9.

[31]See Appendix Table A10.

[32]See Appendix Table A11.

[33]See Appendix Table A12.

[34]See Appendix Table A13.

[35]See Appendix Table A14.

sider imports of country c from country c', instrumented with country-c unweighted tariffs on products from c'.[36] We find that both the effect of trade on economic activity at the border ($\hat{\beta}_1$ of equation 7) and the effect on the gradient from the border ($\hat{\beta}_2$) are somewhat less stable and less precisely estimated for imports than for exports.[37] This is consistent with a mechanism working through export-oriented production in border regions rather than through an increase in consumer access. We explore such a mechanism in Section 6.2 below.

5.3 Heterogeneous effects

We now take advantage of the wide coverage of our data to explore the extent to which our results estimated for the world as a whole also hold for subsets of countries. We focus on two natural sample divisions: developing versus advanced economies, and rural versus urban roads.

5.3.1 Effects by world region

When splitting the sample into advanced and developing economies, we attribute countries to the 'advanced' category if they were classified as 'high income' in the World Bank's 2015 country classification (GNI per capita above USD 12,476). According to this definition, our sample contains 24 advanced and 66 developing economies.

We report these separate estimates in Table 4, focusing on-road grid cells, for which the world-wide estimations have yielded the strongest effects. The signs of our estimated coefficients are consistent with the baseline results in the advanced-economy subsample: bilateral exports growth brightens up locations in borders regions, and all the more so the closer these locations are situated to the border. In the developing-economy subsample, the OLS results are also consistent with our baseline estimates, albeit smaller in magnitude. The IV results, however, turn out not to be statistically significant. These differences are consistent with attenuation bias arising from noisy measurement of export flows and applied tariffs in developing economies, where typically a larger share of trade is informal than in advanced economies (see, e.g., Golub, 2015).

As a further heterogeneity test, we have subdivided our sample by continent.[38] Statistically significant negative coefficients are found on our variable of main interest, the interaction term of bilateral exports and distance from the border, in Asia, Europe and North America, while most estimates for Africa and Latin America are

[36] Own-country tariffs, even though plausibly exogenous in many cases with respect to economic conditions in individual border regions, are a less convincing instrument than neighbor-country tariffs.
[37] See Appendix Table A15.
[38] See Appendix Table A16.

Table 4: Advanced vs. developing economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:								
Light intensity by grid cell and year (Y_{it})	Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}	
	OLS	IV	Poisson	Poisson IV	OLS	IV	Poisson	Poisson IV
Panel A: Advanced economies								
Bilateral exports (in logs)					0.387^{***}	0.540^{***}	0.178^{***}	0.287^{**}
					(0.102)	(0.207)	(0.064)	(0.136)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.072^{***}	-0.126^{***}	-0.030^{***}	-0.030^{**}	-0.050^{***}	-0.125^{***}	-0.018	-0.018
	(0.015)	(0.029)	(0.011)	(0.016)	(0.016)	(0.031)	(0.012)	(0.017)
K-P F statistic		61.11				23.46		
S-W F statistic (main effect)						53.60		
S-W F statistic (interaction)		61.11				61.87		
# Clusters	904	904	904	904	904	904	904	904
# Observations	161,703	161,703	161,703	161,703	161,703	161,703	161,703	161,703
Panel B: Developing economies								
Bilateral exports (in logs)					0.023^{***}	0.145	0.062^{**}	0.058
					(0.009)	(0.126)	(0.027)	(0.040)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.006^{**}	0.001	-0.009^{*}	-0.010	-0.008^{***}	-0.010	-0.010^{*}	-0.011
	(0.002)	(0.012)	(0.005)	(0.008)	(0.002)	(0.013)	(0.006)	(0.009)
K-P F statistic		46.84				2.07		
S-W F statistic (main effect)						5.88		
S-W F statistic (interaction)		46.84				61.62		
# Clusters	2,731	2,731	2,731	2,731	2,731	2,731	2,731	2,731
# Observations	193,961	193,961	193,961	193,961	193,961	193,961	193,961	193,961
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

*** p<0.01, ** p<0.05, * p<0.1
On-road grid cells only. Definition of advanced and developing economies according to the 2015 World Bank classification.
Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

not statistically significant. These results mirror the differences we find when splitting the sample into advanced and developing economies.

5.3.2 Urban and rural roads

Another plausible source of heterogeneity is urbanization: cities may be affected differently from rural locations. Such differences could arise for multiple reasons, including different sectoral specialization, different skill abundance, different availability of trading infrastructure, and agglomeration effects. Existing empirical studies seem to support the hypothesis that access to cross-border trade favors rural regions and smaller cities more than large cities, but these studies are all based on individual countries.[39]

We therefore distinguish 'urban' roads from 'rural' roads. Roads are defined as urban if anywhere within 300 kilometers from the border they reach a city with a

[39] Redding and Sturm (2008) show that population growth of smaller intra-German border towns suffered relatively more from Cold War partition than population growth of larger towns. Baum-Snow *et al.* (2019) find that population and GDP of non-primate Chinese prefectures grew more strongly than those of primate prefectures as a result of improved access to major sea ports. Studying Austria after the raising of the Iron Curtain, Brülhart, Carrère and Robert-Nicoud (2018) find that below-average sized border towns experienced above-average employment growth.

population of at least 500,000.[40] For urban roads, we do not consider segments that lie between the first city reached when travelling inland from the border and the 300 kilometer cut-off, and the grid cells covering the city itself are also excluded. According to this definition, 63% of sample grid cells belong to urban roads.

Table 5: Urban vs. rural roads (500k)

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}	
	OLS	IV	Poisson	Poisson IV	OLS	IV	Poisson	Poisson IV
Bilateral exports (in logs)					0.064***	0.301**	0.104***	0.108***
					(0.012)	(0.133)	(0.026)	(0.039)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.021***	-0.040***	-0.022***	-0.023***	-0.021***	-0.049***	-0.021***	-0.018***
	(0.003)	(0.011)	(0.005)	(0.007)	(0.003)	(0.013)	(0.006)	(0.008)
Urban road (dummy) × Bilateral exports (in logs)	-0.041***	-0.095***	-0.056***	-0.054***	-0.045***	-0.073**	-0.060***	-0.057***
	(0.009)	(0.028)	(0.013)	(0.017)	(0.009)	(0.034)	(0.014)	(0.020)
Urban road (dummy) × Distance from border × Bil. exports	0.011*	0.030	0.016**	0.018*	0.010*	0.011	0.013	0.015
	(0.006)	(0.019)	(0.008)	(0.011)	(0.006)	(0.023)	(0.009)	(0.012)
K-P F statistic		15.22				2.95		
S-W F statistic (main effect)						26.27		
S-W F statistic (Exp x Dist interaction)		80.46				94.32		
S-W F statistic (Exp x Urb interaction)		60.14				81.31		
S-W F statistic (triple interaction)		107.30				124.56		
# Clusters	3,633	3,633	3,633	3,633	3,633	3,633	3,633	3,633
# Observations	354,885	354,885	354,885	354,885	354,885	354,885	354,885	354,885
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

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

On-road grid cells only. Urban road defined as road that leads to a city with at least 500,000 inhabitants.

Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

We estimate on-road-cell models analogous to our baseline equations (6 and 7), adding interaction terms of distance and exports with a dummy for urban roads. Table 5 reports our results. Those estimates consistently suggest that border locations experience weaker lights growth after bilateral export expansion if they are close to a city in their own country. The effect of exports on lights at the border appears to be around twice as strong for rural roads as for urban roads. These estimates, although somewaht noisy, imply that rural border regions stand to benefit comparatively more from trade liberalization than urban border regions, which is in line with previous empirical findings.

6 Extensions

6.1 Income and population effects

Our main dependent variable, total light emissions per grid cell and year, has the advantage of being precisely measured with constant reliability across time and space. An important limitation of this variable, however, is that we cannot distinguish between population and income effects: do brighter lights associated with intensified

[40]Data on the location of cities are taken from Natural Earth. Appendix Table A18 shows results based on an alternative population cut-off of 100,000. The qualitative results are very similar.

trade reflect the migration of people towards border regions, do they reflect higher per-capita incomes in border regions, or do they reflect a combination of both? In Appendix A, we show that within the framework of the quantitative spatial model our coefficients of interest have the same expected signs irrespective of whether night lights are measuring population or output. Nevertheless, the distinction is of interest empirically.

In order to address this question, we combine the lights data with gridded population data, which are available at the same 10×10 kilometer resolution as the one we choose for our analyses based on lights only.[41]

In Table 6, we show estimates of our specification (7) with lights per capita and population as altenative dependent variables. These estimates are less stable and precise than our baseline regressions, but the qualitative results remain. The evidence suggests that both per-capita lights and populations of border regions respond positively to cross-border export expansion. However, the estimates are too imprecise for us to credibly quantify the relative weight of the two response variables.

Table 6: Light intensity per capita and population

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Lights (logs) OLS	(2) IV	(3) Lights per capita (logs) OLS	(4) IV	(5) Population (logs) OLS	(6) IV
Bilateral exports (in logs)	0.017***	0.043	0.005***	0.014	0.005	-0.053
	(0.003)	(0.072)	(0.001)	(0.036)	(0.007)	(0.081)
Bilateral exports (in logs) $\times$ Distance from border (in 100km)	-0.006***	-0.006	-0.003***	0.001	0.003	-0.016*
	(0.001)	(0.004)	(0.001)	(0.003)	(0.002)	(0.009)
K-P F statistic		1.01		1.01		1.01
S-W F statistic (main effect)		7.60		7.60		7.60
S-W F statistic (interaction)		54.57		54.57		54.57
# Clusters	3,573	3,573	3,573	3,573	3,573	3,573
# Observations	792,204	792,204	792,204	792,204	792,204	792,204
Grid cell FE	X	X	X	X	X	X
Country-year FE	X	X	X	X	X	X

*** p<0.01, ** p<0.05, * p<0.1
On-road + off-road grid cells. Two-way clustered standard errors at cell and region-year level in parentheses.

6.2 A mechanism: increased border-region production

We observe that bilateral exports favor the economic development of locations close to the relevant land border, while the impact of imports is more muted. A natural interpretation of this finding is that development takes the form of export-oriented production that is stimulated in border regions. However, other mechanisms could be at play. Two evident alternative scenarios are (a) that increased activity observed near borders might stem primarily from non-traded services that support trading activities, and (b) that we observe the result of redistributive policies aimed at spreading

[41]Due to incomplete coverage of the population data, we thereby lose some 15% of the data sample. See Appendix B for details.

trade-related gains towards border regions through public spending.

In order to explore the mechanism behind the estimated trade effects, we focus on the link between agricultural exports and the development of agriculture-dependent border regions. The reason for focusing on agriculture is that there exists fine-grained spatial information on production in that sector (Monfreda et al. 2008), of a kind that is not available for manufacturing or services. This allows us to relate localized production to product-level export data, which in turn makes it possible to explore whether trade expansion is particularly beneficial to border-region development if it occurs in a product the region is specialized in.

Specifically, we can draw on geo-referenced data on the cultivation of 10 different crops at a resolution of 10 $\times$ 10 kilometers. This information allows us to establish the proportion of land occupied by each crop in each 10 $\times$ 10 kilometer grid cell. We use these proportions as weights.[42]

Table 7: Trade in local crops

Dependent variable: Light intensity: $\ln(Y_{it}+1)$	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
Bilateral weighted crop exports (in logs)				0.113***		0.112**
				(0.042)		(0.046)
Bilateral weighted crop exports (in logs) × Distance from border (in 100km)	-0.032***		-0.034**	-0.023***		-0.027
	(0.008)		(0.015)	(0.007)		(0.019)
			Effects of overall exports			
Bilateral exports (in logs)					0.090	-0.472*
					(0.377)	(0.274)
Bilateral exports (in logs) × Distance from border (in 100km)		-0.005	0.002		-0.007	0.011
		(0.007)	(0.010)		(0.010)	(0.015)
K-P F statistic	70.09	32.04	9.28	3.61	0.43	1.58
S-W F statistic (main effect: crop)				10.89		22.27
S-W F statistic (interaction: crop)	70.09		14.07	65.61		15.97
S-W F statistic (main effect: total exports)					0.88	4.08
S-W F statistic (interaction: total exports)		32.04	15.67		15.04	14.94
# Clusters	5,768	5,768	5,768	5,772	5,772	5,772
# Observations	506,931	506,931	506,931	506,939	506,939	506,939
Grid cell FE	X	X	X	X	X	X
Country-pair-year FE	X	X	X			
Country-year FE				X	X	X

On-road grid cells only. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table 7 describes the results of estimating equation (7), using weighted exports of crops grown in cell i to neighbor country c' as an alternative bilateral export variable. We instrument for this additional variable by weighting import tariffs of country c' on these crops. As a complementary instrument, we use weighted world prices of these crops, the identifying assumption being that each cell is too small to influence the world price. Column (1) shows that growth in bilateral exports of locally-grown crops flatten the border-region light gradients. In contrast, the impact of overall ex-

[42]For a list of crops in the sample, see Appendix Table A19. See Appendix B for details on the data. In these estimations, we do not apply the sample restriction based on asymmetric tariff changes described in Section 4.2 and applied in the preceding analyses, as this would shrink the crops sample by around 99%.

ports becomes statistically insignificant when estimated for the same, predominantly agricultural, sample of regions (column 2). When we consider local crop exports and overall exports simultaneously (column 3), changing light gradients turn out to be driven entirely by exports of local crops. Our findings suggest that the stimulation of local production is a significant mechanism behind the trade-induced growth of border-region economies.

7 Conclusion

Our estimates based on world-wide spatially disaggregated data suggest that bilateral trade expansion encourages economic development in the vicinity of land borders. To the extent that border regions are less developed than interior regions, this implies a spatially equalizing effect of international trade. Based on detailed information on agricultural production and trade, we moreover find that trade-related development of border regions is at least in part driven by local export-oriented production.

Turning to the implications of our findings for theoretical models, we note that the flattening of the border shadow when trade increases is consistent with weak agglomeration forces and/or strong congestion forces. Our findings can be interpreted as evidence that parameters in spatial models are such that multiple equilibria are unlikely.

Our results also show that land borders are, in themselves, factors of remoteness. This is a striking result in view of the finding e.g. by Henderson *et al.* (2012) that, contrary to perceptions, inland areas in Sub-Saharan Africa have not grown more slowly than coastal areas. Combining their observation and ours suggests that it may not be landlockedness that holds back economic development, but rather proximity to borders. Despite of modernization efforts, many borders in the developing world continue to be very costly to cross.

Night lights have been shown elsewhere to be a reliable proxy for local output. Nonetheless, they are an imperfect measure. Most importantly, as we do not observe wages and local prices and our approach is reduced form, we cannot make rigorous statements on local welfare, nor on distributional and incidence effects.[43]

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A Theory details

This appendix provides derivations relevant for the model outlined in Section 2. We show results for a model where labor is fully mobile only within a country (when labor is mobile everywhere, Allen and Arkolakis (2014) provide all necessary derivations to reach equation (1) in the main text).

Link between the price index and outcomes proxied by night lights There are N locations i, distributed across two different countries C. Agents are fully mobile within the country and have preferences as described in Section 2. Given the CES preference assumption and perfect competition in an Armington setting, the price index in location i is given by:

$$P_i^{1-\sigma} = \sum_j \left(\tau_{ji} \frac{w_j}{A_j} \right)^{1-\sigma}.$$

Balanced trade implies that

$$w_i L_i = \left(\frac{w_i}{A_i} \right)^{1-\sigma} \underbrace{\sum_j (\tau_{ij})^{1-\sigma} \frac{w_j L_j}{P_j^{1-\sigma}}}_{PMA_i}.$$

As in Donaldson and Hornbeck (2016), we have that $P_i^{1-\sigma} = PMA_i$ under symmetric trade costs. Free movement within a country ensures that welfare is equalized, so that

$$W_i = \frac{w_i}{P_i} \bar{u}_i L_i^{\beta} = \begin{cases} W_1 & i \in 1 \\ W_2 & i \in 2 \end{cases},$$

where population across locations within a country sums to the country's (exogenous) total population: $\sum_{i \in C} L_i = L_C$. Combining the preceding equations leads to the following equilibrium system of equations:

$$\begin{aligned} w_i L_i &= \left(\frac{w_i}{\bar{A}_i L_i^{\alpha}} \right)^{1-\sigma} P_i^{1-\sigma}, \\ P_i^{1-\sigma} &= \sum_j \left(\tau_{ji} \frac{w_j}{\bar{A}_j L_j^{\alpha}} \right)^{1-\sigma}, \\ W_i^{\frac{1}{\beta}} &= \left(\frac{w_i}{P_i} \bar{u}_i \right)^{\frac{1}{\beta}} L_i = \begin{cases} W_1^{\frac{1}{\beta}} & i \in 1 \\ W_2^{\frac{1}{\beta}} & i \in 2 \end{cases}, \\ \sum_{i \in C} L_i &= L_C. \end{aligned} \tag{8}$$

Rearranging, one can get the following expressions for population, (real) wages and (real) output of location i:

$$L_i^{(1-\alpha(\sigma-1)-\beta\sigma)} = \left(\bar{A}_i\right)^{(\sigma-1)} \left(W_{R(i)}\right)^{-\sigma} \left(P_i\right)^{1-2\sigma} \left(\bar{u}_i\right)^{\sigma}, \tag{9}$$

$$\left(\frac{w_i}{P_i}\right)^{1-\alpha(\sigma-1)-\beta\sigma} = \left(\bar{A}_i\right)^{-\beta(\sigma-1)} \left(\bar{u}_i\right)^{-(1-(\sigma-1)\alpha)} \left(W_{R(i)}\right)^{1-(\sigma-1)\alpha} P_i^{-\beta(1-2\sigma)}, \tag{10}$$

$$\left(\frac{Y_i}{P_i}\right)^{1-\alpha(\sigma-1)-\beta\sigma} = \left(\bar{A}_i\right)^{(1-\beta)(\sigma-1)} \left(\bar{u}_i\right)^{\sigma-(1-(\sigma-1)\alpha)} \left(W_{R(i)}\right)^{1-(\sigma-1)\alpha-\sigma} P_i^{(1-\beta)(1-2\sigma)}. \tag{11}$$

For any plausible value of the trade elasticity $(\sigma - 1)$, we have that $1 - 2\sigma < 0$, so that equation (9) implies that the population in location i is negatively correlated with the price index if $\gamma_1 = 1 - \alpha(\sigma - 1) - \beta\sigma > 0$. Furthermore, with $\beta < 0$ as is standard in the literature, equation (10) implies that the real wage is negatively correlated with the price index and equation (11) implies that total real output is also negatively correlated with the price index. Equation (1) in Section 2 shows that this is true for nominal output as well. As a result, whether night lights are a proxy for population, the real wage, real output, or nominal wages and output, does not change the interpretation of the sign of the coefficient in our regressions.

Negative relationship between export share and distance to border Equation 3 can be rewritten as an infinite sum that converges if $|\gamma_2/\gamma_1| < 1$:[44]

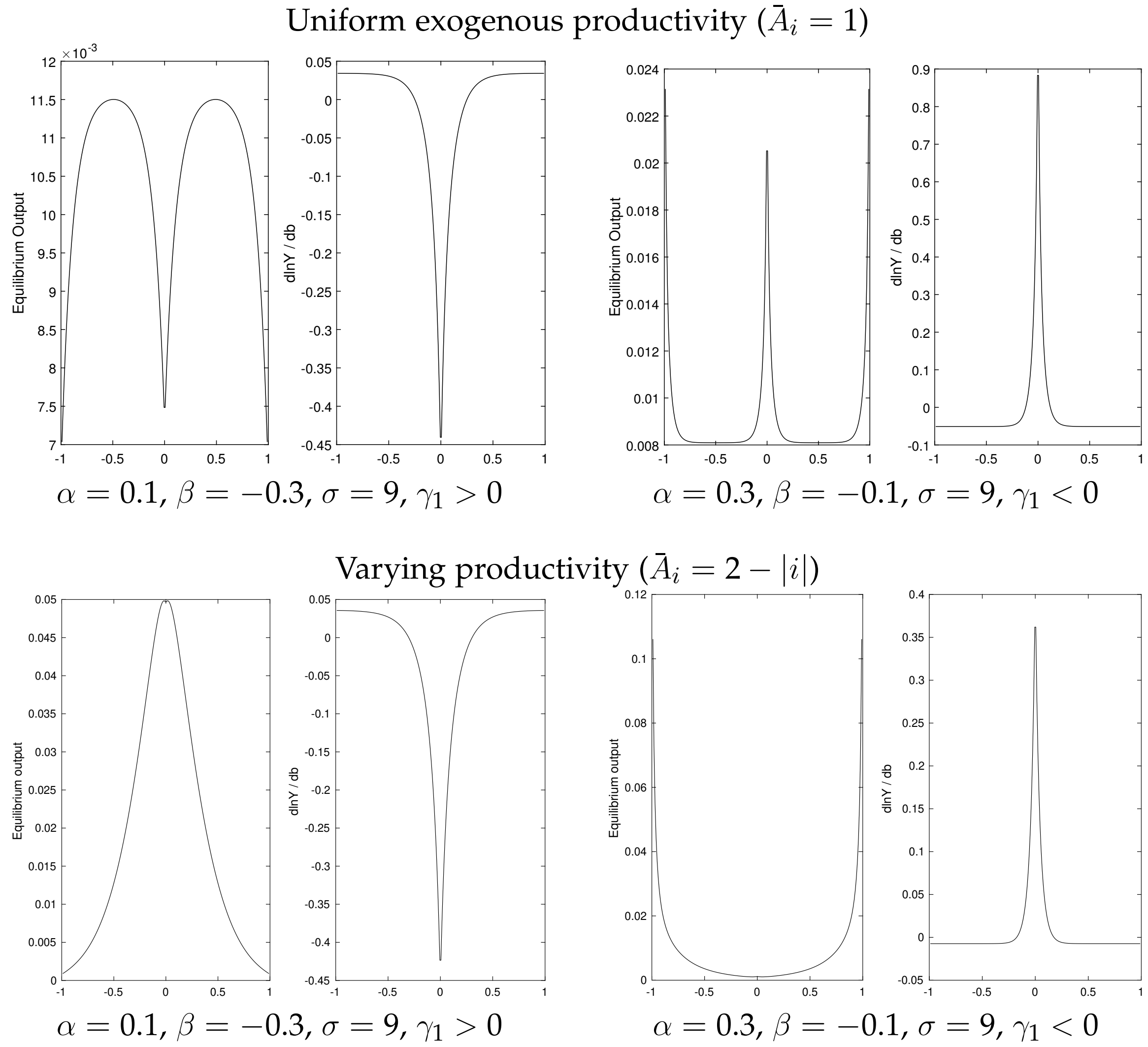
$$\frac{\partial \ln P_i^{1-\sigma}}{\partial b} = (1-\sigma)\left[\frac{X_{i,C_2}}{Y_i} + \underbrace{\frac{\gamma_2}{\gamma_1}\sum_j \frac{X_{ij}}{Y_i}\frac{X_{j,C_{-j}}}{Y_j} + \left(\frac{\gamma_2}{\gamma_1}\right)^2 \sum_j \left(\frac{X_{ij}}{Y_i}\right)^2 \frac{X_{j,C_{-j}}}{Y_j} + \dots}_{\text{higher-order terms}}\right].$$

Ignoring the higher-order terms, we can approximate the change in the price index of region i with its share of exports ($\frac{X_{i,C_2}}{Y_i}$), which we can in turn approximate with the location's distance to the border, since we have that:

$$\frac{X_{i,C_2}}{Y_i} = \exp\left((1-\sigma)\beta d_i^{border}\right) \frac{\sum_{j\in C_2} \exp\left(b + \beta d_j^{border}\right)^{1-\sigma} Y_j/P_j^{1-\sigma}}{\sum_j \tau_{ij}^{1-\sigma} Y_j/P_j^{1-\sigma}},$$

[44] The equation is similar to a Leontief inverse, rewriting equation 3 in matrix notation: $\Delta P^{1-\sigma} = (1-\sigma)E + \frac{\gamma_2}{\gamma_1} M \Delta P^{1-\sigma}$, where $\Delta P^{1-\sigma}$ is the vector of elasticities, E is the vector of export shares, and M is the matrix of exports divided by total output. Rewriting yields $\Delta P^{1-\sigma} = (1-\sigma)(1-\frac{\gamma_2}{\gamma_1}M)^{-1}E$, where the Leontief inverse $(1-\frac{\gamma_2}{\gamma_1}M)^{-1}$ can be rewritten as an infinite sum.

Figure 6: Spatial equilibrium and border effect on a line



Note: The figure displays the equilibrium output on the line economy, for different parameter values. In each panel, the left side displays the spatial distribution of output. The right side displays the elasticity of output with respect to the border cost. When $\gamma_1 > 0$, the elasticity is consistent with a border shadow.

so that the share of exports in output is negatively correlated with the distance to the border.[45]

Simulations for the line economy To simulate the line economy and produce Figure 1 in the body of the paper, we assume that locations lie on a line between -1 and 1, with a border at 0. Trade costs are given by $\tau_{ij} = \exp\{\tau|i-j| + b\,(\text{sign}(i) \neq \text{sign}(j))\}$.

[45]By ignoring higher order term, we miss out on some general equilibrium terms. However, these terms would likely reinforce the correlation between $\frac{\partial \ln P_i^{1-\sigma}}{\partial b}$ and the distance to the border, because $\frac{X_{ij}}{Y_i}$ is higher for regions closeby. Since locations close to the border are closer to other locations closer to the border, the importance of the proximity to the border will be reinforced. All the simulations we tried show that indeed, location closer to the border experience a decrease in market access when the border cost increases, even in cases where $|\gamma_2/\gamma_1| > 1$.

We choose $\tau = 1$, $b = 0.1$, $\sigma = 9$ and set exogenous amenities equal to 1 in all locations. We then solve the model numerically for various elasticities and exogenous productivities to illustrate the border shadow.

Figure 6 displays results for different parameter combinations. The first row shows results for spatially equal exogenous productivities, and the second row shows results for exogenous productivities that are higher closer to the border. The left panels show the case when $\gamma_1 > 0$ and the right panels when $\gamma_1 < 0$. Each panel is composed of two subfigures, with equilibrium output on the left and the semi-elasticity of output with respect to border cost on the right. When $\gamma_1 > 0$, the change in output is always more negative close to the border when the border cost increases. In contrast, the presence of a border shadow in the equilibrium output in level does not necessarily imply that $\gamma_1 > 0$: the second row shows no border shadow when $\gamma_1 > 0$ because the exogenous productivities are higher around the border, compensating for the border cost. Nevertheless, the border shadow is present in the elasticity of output with respect to the border cost.

B Data sources

We use the data on *night lights* from the Earth Observation Group (EOG, Payne Institute for Public Policy, Colorado School of Mines. DMSP data collected by the US Air Force Weather Agency). We use "Version 4 DMSP-OLS Nighttime Lights Time Series", available at eogdata.mines.edu/products/dmsp/. The collection and cleaning of night lights data recorded by satellites is a five-step process that includes cloud masking, filtering out of light signals (radiance) from ambient "noise", aggregation and geo-referencing, filtering in terms of persistence (to exclude e.g. flares of lightning and fires), and quantifying radiance on a bounded scale ranging from zero to 63. Dropping cells featuring lights emitted by gas flares – using readily available information on their location (see Henderson, Storeygard and Weil, 2012) – has no discerinble impact on our results. Raw light values are intercalibrated between years, to account for the fact that different satellites were used over time. Coefficients used for intercalibration are made available by the Earth Observation Group together with the night lights data. They were originally proposed by Elvidge *et al.* (2009). We attribute 0 to grid cells that become negative after calibration, and we attribute 63 to grid cells that exceed this value after calibration. While the 0-63 scale represents the luminosity of light proportionally, pixels with the value of 63 may be top censored. This on average concerns some 0.2% of pixels in our sample mostly in advanced-economy cities. By contrast, the proportion of zero-light pixels is high in developing countries, ranging from an average of 57% in South Asia to 92% in Sub-Saharan Africa before calibration. After calibration, share of precise zeros falls to 12% for South Asia and 19% for Sub-Saharan Africa.

Data on *population* counts are taken from WorldPop (hub.worldpop.org), a research program based in the University of Southampton. The dataset contains globally consistent population information by grid cell, drawn from a combination of national censuses for varying sub-national units (municipalities, census tracts, etc.) as well as different variables derived from stallelite images. The finest available grid-cell resolution is 30 arc-seconds, or around 1 kilometer at the equator. Gridded population data are available from 2000 onwards.

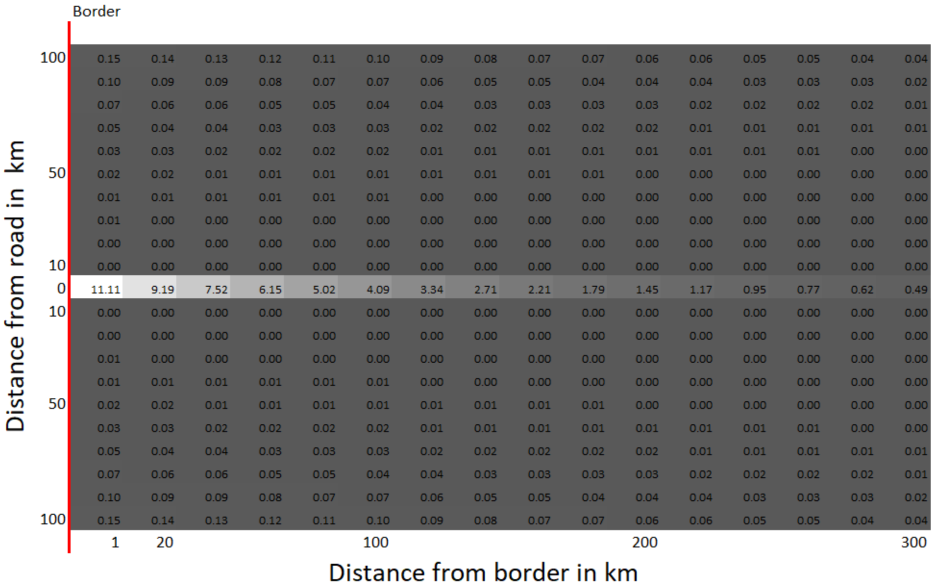
To measure *trade* liberalization, we draw on bilateral export volumes and simple average applied tariff rates between neighboring countries from the United Nations' UN Comtrade database and the UNCTAD Trade Analysis and Information System (TRAINS) database (accessed through the WITS platform). For all trade variables, if a data point is not available for a specific year, we take the value from the preceding year as the value for the missing year. If the information is also missing for the preceding year, we take the value for the subsequent after. The data point is considered as missing only if no value is available inside this 3-year window.

Georeferenced data on the location of national and state *borders* are taken from the Database of Global Administrative Areas hosted by the Hijmans Lab at UC Davis. Data on *roads* are obtained from the 2011 ESRI World Roads dataset.

Finally, worldwide data on harvested areas of 10 *crops* are obtained from Monfreda *et al.* (2008) in 10 × 10 kilometer grid format. The authors use satellite data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Satellite Pour l'Observation de la Terre (SPOT) to produce a precise global dataset of agricultural land use in the year 2000. The dataset is constructed from two different satellite datasets on land cover and then combined with data from agricultural censuses and FAO data. The data can be downloaded from EarthStat (earthstat.org). Appendix Table A19 lists the crops considered and provides summary statistics. Data on the world price of these crops are taken from FRED and from the World Bank Commodity Price Data.

C Appendix figures and tables

Figure A1: Predicted absolute change in light intensity associated with a 10% increase in exports



Note: The graph shows predicted absolute changes in light intensity after a 10% increase in exports starting from a scenario with trade set to the mean value in our data, based on separate regressions for on-road and off-road grid cells, with grid cell and country-year fixed effects, and exports instrumented with tariffs. Darker colors symbolize lower light growth.

Table A1: Correlation between night lights and regional GDP

	(1) ln(GDP)	(2) ln(GDP)	(3) ln(GDP)	(4) ln(GDP)
ln(Light intensity)	0.498***	0.333***	0.167***	0.036***
	(0.0279)	(0.00747)	(0.0143)	(0.0129)
# Observations	4,966	4,913	4,913	4,903
R-squared	0.203	0.977	0.992	0.997
Within R2		0.235	0.058	0.005
Region FE		X	X	X
Year FE			X	
Country-year FE				X

Standard errors clustered at the NUTS3 region-level in parentheses.
GDP (in purchasing power standards PPS) taken from Eurostat's series NAMA_10R_3GDP. Included years: 2000, 2005, 2010 and 2013.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Summary statistics: baseline sample (on-road and off-road grid cells)

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	3.70	6.64	0	63	937,612
Distance from border	146.38	84.51	0.00	300	937,612
Total exports to neighbor country (in 100 mio US dollar)	407.66	812.82	0.00	3,006.86	937,612
Simple average applied tariff rate	7.59	8.29	0	81.03	937,612
Population count (people/grid cell)	5,451.10	29,162.18	0	3,473,122	826,314
Dummy for light = 0	0.07	0.26	0	1	937,612

Table A3: Summary statistics: on-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	6.45	9.56	0	63	355,664
Distance from border	139.43	85.30	0.00	300	355,664
Total exports to neighbor country (in 100 mio US dollar)	409.35	809.65	0.00	3,006.86	355,664
Simple average applied tariff rate	7.36	8.71	0	81.03	355,664
Population count (people/grid cell)	10,710.61	45,187.92	0	3,473,122	315,767
Dummy for light = 0	0.04	0.20	0	1	355,664

Table A4: Summary statistics: off-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	2.01	2.77	0	63	581,948
Distance from border	150.64	83.75	0.00	300	581,948
Total exports to neighbor country (in 100 mio US dollar)	406.63	814.75	0.00	3,006.86	581,948
Simple average applied tariff rate	7.74	8.02	0	81.03	581,948
Population count (people/grid cell)	2,198.16	9,263.22	0	326,600.30	510,547
Dummy for light = 0	0.09	0.28	0	1	581,948

Table A5: Baseline estimates in levels

	(1)	(2)	(3)	(4)
Dependent variable: Light intensity by grid cell and year (Y_{it})	OLS	IV	OLS	IV
Panel A: On-road grid cells only				
Bilateral exports (in logs)			0.326***	0.037
			(0.084)	(1.065)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.076***	-0.184***	-0.065***	-0.120
	(0.025)	(0.059)	(0.024)	(0.080)
K-P F statistic		65.32		5.90
S-W F statistic (main effect)				23.16
S-W F statistic (interaction)		65.32		82.84
# Clusters	3,635	3,635	3,635	3,635
# Observations	355,664	355,664	355,664	355,664
Panel B: Off-road grid cells only				
Bilateral exports (in logs)			0.069***	0.101
			(0.017)	(0.134)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.021***	-0.073***	-0.014**	-0.060***
	(0.007)	(0.023)	(0.007)	(0.022)
K-P F statistic		54.82		5.53
S-W F statistic (main effect)				89.43
S-W F statistic (interaction)		54.82		57.03
# Clusters	3,455	3,455	3,456	3,456
# Observations	581,945	581,945	581,948	581,948
Panel C: On-road + off-road grid cells				
Bilateral exports (in logs)			0.156***	0.096
			(0.035)	(0.309)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.050***	-0.131***	-0.037***	-0.101**
	(0.012)	(0.038)	(0.011)	(0.039)
K-P F statistic		66.34		5.70
S-W F statistic (main effect)				65.39
S-W F statistic (interaction)		66.34		70.39
# Clusters	3,872	3,872	3,873	3,873
# Observations	937,609	937,609	937,612	937,612
Grid cell FE	X	X	X	X
Country-pair-year FE	X	X		
Country-year FE			X	X

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

Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A6: Advanced vs. developing economies in levels

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A: Advanced economies				
Bilateral exports (in logs)			2.063***	-1.306
			(0.629)	(2.513)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.481***	-0.519***	-0.324***	-0.428**
	(0.100)	(0.169)	(0.107)	(0.199)
K-P F statistic		61.11		23.46
S-W F statistic (main effect)				53.60
S-W F statistic (interaction)		61.11		61.87
# Clusters	904	904	904	904
# Observations	161,703	161,703	161,703	161,703
Panel B: Developing economies				
Bilateral exports (in logs)			0.166**	1.457*
			(0.075)	(0.822)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.002	-0.077	-0.014	-0.111
	(0.022)	(0.059)	(0.021)	(0.070)
K-P F statistic		46.84		2.07
S-W F statistic (main effect)				5.88
S-W F statistic (interaction)		46.84		61.62
# Clusters	2,731	2,731	2,731	2,731
# Observations	193,961	193,961	193,961	193,961
Grid cell FE	X	X	X	X
Country-pair-year FE	X	X		
Country-year FE			X	X

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

On-road grid cells only. Definition of advanced and developing economies according to the 2015 World Bank classification. Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A7: Baseline estimates, without sample restriction

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Levels: Y_{it} OLS	(2) Logs: $ln(Y_{it}+1)$ OLS	(3) Levels: Y_{it} Poisson	(4) Levels: Y_{it} OLS	(5) Logs: $ln(Y_{it}+1)$ OLS	(6) Levels: Y_{it} Poisson
Panel A: On-road grid cells only						
Bilateral exports (in logs)				0.033*	0.011***	0.024***
				(0.018)	(0.003)	(0.006)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.005	-0.006***	-0.009***	-0.014	-0.007***	-0.013***
	(0.009)	(0.001)	(0.002)	(0.009)	(0.002)	(0.003)
# Clusters	9,007	9,007	9,006	9,011	9,011	9,011
# Observations	945,860	945,860	945,541	945,868	945,868	945,868
Panel B: Off-road grid cells only						
Bilateral exports (in logs)				0.013**	0.006***	0.033***
				(0.005)	(0.001)	(0.008)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.007***	-0.002***	-0.013***	-0.005**	-0.002***	-0.011***
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
# Clusters	8,602	8,602	8,578	8,605	8,605	8,600
# Observations	1,418,810	1,418,810	1,406,773	1,418,828	1,418,828	1,418,804
Panel C: On-road + off-road grid cells						
Bilateral exports (in logs)				0.020**	0.007***	0.029***
				(0.009)	(0.002)	(0.006)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.008*	-0.003***	-0.010***	-0.009**	-0.003***	-0.010***
	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)
# Clusters	9,443	9,443	9,441	9,443	9,443	9,443
# Observations	2,364,687	2,364,687	2,362,840	2,364,696	2,364,696	2,364,696
Grid cell FE	X	X	X	X	X	X
Country-pair-year FE	X	X	X			
Country-year FE				X	X	X

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

Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A8: First stage estimate

	(1)
Dependent variable: Log of bilateral exports X Distance from border (in 100km)	
Average applied tariff rate X Distance from border (in 100km)	-0.038***
	(0.005)
# Clusters	3,872
# Observations	937,609
Grid cell FE	X
Country-pair-year-FE	X

*** p <0.01, ** p <0.05, * p <0.1.
On-road + Off-road grid cells .Clustered standard errors at country-pair level in parentheses.

Table A9: Baseline estimates, varying distance cut-offs

Dependent variable: Light intensity: log(Y_{it} + 1)	(1) IV 300km	(2) IV 250km	(3) IV 200km	(4) IV 150km	(5) IV 300km	(6) IV 250km	(7) IV 200km	(8) IV 150km
Bilateral exports (in logs)					0.282**	0.263*	0.261*	0.200
					(0.135)	(0.136)	(0.138)	(0.131)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.029**	-0.024*	-0.039**	-0.050*	-0.040***	-0.032**	-0.044**	-0.054*
	(0.012)	(0.014)	(0.016)	(0.028)	(0.014)	(0.016)	(0.019)	(0.031)
K-P F statistic	65.32	57.98	48.57	48.14	5.90	5.36	4.89	4.45
S-W F statistic (main)					23.16	22.65	20.43	15.39
S-W F statistic (interaction)	65.32	57.98	48.57	48.14	82.84	67.87	51.71	52.05
# Clusters	3,635	3,462	3,274	3,000	3,635	3,462	3,274	3,000
# Observations	355,664	307,048	253,790	197,951	355,664	307,048	253,790	197,951
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

On-road grid cells only. *** p <0.01, ** p <0.05, * p <0.1.
Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A10: Baseline estimates, excluding border-crossing grid cells

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Logs: ln($Y_{it}+1$) OLS	(2) IV	(3) Levels: Y_{it} Poisson	(4) Poisson IV	(5) Logs: ln($Y_{it}+1$) OLS	(6) IV	(7) Levels: Y_{it} Poisson	(8) Poisson IV
Panel A: On-road grid cells only								
Bilateral exports (in logs)					0.052***	0.284**	0.085***	0.089**
					(0.012)	(0.135)	(0.025)	(0.038)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.017***	-0.030**	-0.016***	-0.017**	-0.015***	-0.041***	-0.014***	-0.016**
	(0.003)	(0.012)	(0.005)	(0.007)	(0.003)	(0.014)	(0.005)	(0.007)
K-P F statistic		64.87				5.91		
S-W F statistic (main effect)						23.54		
S-W F statistic (interaction)		64.87				82.40		
# Clusters	3,625	3,625	3,625	3,625	3,625	3,625	3,625	3,625
# Observations	353,673	353,673	353,673	353,673	353,673	353,673	353,673	353,673
Panel B: Off-road grid cells only								
Bilateral exports (in logs)					0.020***	0.055*	0.104***	0.110***
					(0.004)	(0.030)	(0.022)	(0.032)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.008***	-0.015**	-0.037***	-0.037***	-0.007***	-0.015**	-0.031***	-0.032***
	(0.001)	(0.007)	(0.007)	(0.010)	(0.001)	(0.006)	(0.007)	(0.010)
K-P F statistic		54.82				5.53		
S-W F statistic (main effect)						89.43		
S-W F statistic (interaction)		54.82				57.03		
# Clusters	3,456	3,456	3,454	3,454	3,455	3,455	3,453	3,453
# Observations	581,948	581,948	581,666	581,666	581,945	581,945	581,663	581,663
Panel C: On-road + off-road grid cells								
Bilateral exports (in logs)					0.032***	0.114**	0.095***	0.096***
					(0.006)	(0.053)	(0.022)	(0.033)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.013***	-0.024**	-0.029***	-0.029***	-0.011***	-0.026***	-0.025***	-0.025***
	(0.002)	(0.010)	(0.006)	(0.008)	(0.002)	(0.010)	(0.006)	(0.008)
K-P F statistic		66.15				5.69		
S-W F statistic (main effect)						65.91		
S-W F statistic (interaction)		66.15				70.23		
# Clusters	3,863	3,863	3,862	3,862	3,862	3,862	3,861	3,861
# Observations	935,621	935,621	935,619	935,619	935,618	935,618	935,616	935,616
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

*** p <0.01, ** p <0.05, * p <0.1.
Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

Table A11: Baseline estimates, without small countries

Dependent variable: Light intensity: $\log(Y_{it}+1)$	(1) Baseline IV	(2) No small countries IV	(3) Baseline IV	(4) No small countries IV
Bilateral exports (in logs)			0.282**	0.344*
			(0.135)	(0.187)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.029**	-0.018	-0.040***	-0.037**
	(0.012)	(0.014)	(0.014)	(0.017)
K-P F statistic	65.32	55.02	5.90	3.60
S-W F statistic (main effect)			23.16	16.14
S-W F statistic (interaction)	65.32	55.02	82.84	70.64
# Clusters	3,635	1,407	3,635	1,407
# Observations	355,664	228,207	355,664	228,207
Grid cell FE	X	X	X	X
Country-pair-year FE	X	X		
Country-year FE			X	X

On-road grid cells only. "Small" countries defined as having an area $< 500,000$ km^2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A12: Baseline estimates, country-year level error clustering

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Logs: $\ln(Y_{it}+1)$ OLS	(2) IV	(3) Levels: Y_{it} Poisson	(4) Poisson IV	(5) Logs: $\ln(Y_{it}+1)$ OLS	(6) IV	(7) Levels: Y_{it} Poisson	(8) Poisson IV
Panel A: On-road grid cells only								
Bilateral exports (in logs)					0.051***	0.282	0.083***	0.095**
					(0.018)	(0.212)	(0.026)	(0.049)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.017***	-0.029*	-0.015**	-0.015	-0.015***	-0.040*	-0.014**	-0.013
	(0.005)	(0.017)	(0.007)	(0.010)	(0.005)	(0.021)	(0.007)	(0.011)
K-P F statistic		14.17				1.98		
S-W F statistic (main effect)						10.71		
S-W F statistic (interaction)		14.17				28.59		
# Clusters	308	308	308	308	308	308	308	308
# Observations	355,664	355,664	355,664	355,664	355,664	355,664	355,664	355,664
Panel B: Off-road grid cells only								
Bilateral exports (in logs)					0.020***	0.055	0.104***	0.111**
					(0.007)	(0.039)	(0.032)	(0.050)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.008***	-0.015	-0.037***	-0.040**	-0.007***	-0.015	-0.031**	-0.032*
	(0.003)	(0.011)	(0.013)	(0.017)	(0.003)	(0.011)	(0.012)	(0.016)
K-P F statistic		18.51				2.01		
S-W F statistic (main effect)						31.75		
S-W F statistic (interaction)		18.51				19.31		
# Clusters	312	312	310	310	312	312	310	310
# Observations	581,945	581,945	581,663	581,663	581,948	581,948	581,666	581,666
Panel C: On-road + off-road grid cells								
Bilateral exports (in logs)					0.031***	0.113	0.092***	0.096**
					(0.011)	(0.078)	(0.025)	(0.038)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.013***	-0.024	-0.027***	-0.027**	-0.011***	-0.026	-0.024***	-0.023**
	(0.004)	(0.016)	(0.009)	(0.012)	(0.004)	(0.016)	(0.008)	(0.011)
K-P F statistic		17.76				2.16		
S-W F statistic (main effect)						22.57		
S-W F statistic (interaction)		17.76				21.34		
# Clusters	312	312	311	311	312	312	311	311
# Observations	937,609	937,609	937,607	937,607	937,612	937,612	937,610	937,610
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Two-way clustered standard errors at grid cell and country-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

Table A13: Reduced-form estimates

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1)	(2)	(3)	(4)
	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$	
Average applied tariff rate		-0.007		0.000
		(0.006)		(0.001)
Average applied tariff rate × Distance from border (in 100km)	0.005***	0.004***	0.001**	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)
# Clusters	3,872	3,873	3,872	3,873
# Observations	937,609	937,612	937,609	937,612
Grid cell FE	X	X	X	X
Country-pair-year FE	X		X	
Country-year FE		X		X

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

Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A14: Baseline estimates with alternative instrument

	(1)	(2)	(3)
Dependent variable: Light intensity by grid cell and year (Y_{it})	Levels: Y_{it} IV	Logs: $ln(Y_{it}+1)$ IV	Levels: Y_{it} Poisson IV
Panel A: On-road grid cells only			
Bilateral exports (in logs)	1.824***	0.272***	-0.038
	(0.440)	(0.058)	(0.068)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.324***	-0.066***	0.008
	(0.098)	(0.013)	(0.011)
K-P F statistic	85.50	85.50	
S-W F statistic (main effect)	207.54	207.54	
S-W F statistic (interaction)	171.40	171.40	
# Clusters	1,161	1,161	1,161
# Observations	187,820	187,820	187,820
Panel B: Off-road grid cells only			
Bilateral exports (in logs)	0.514**	0.111***	0.113
	(0.200)	(0.036)	(0.114)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.096***	-0.030***	-0.064**
	(0.027)	(0.006)	(0.027)
K-P F statistic	81.84	81.84	
S-W F statistic (main effect)	214.39	214.39	
S-W F statistic (interaction)	162.76	162.76	
# Clusters	1,162	1,162	1,162
# Observations	276,081	276,081	276,081
Panel C: On-road + off-road grid cells			
Bilateral exports (in logs)	1.161***	0.196***	-0.012
	(0.299)	(0.045)	(0.068)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.235***	-0.054***	-0.005
	(0.059)	(0.010)	(0.017)
K-P F statistic	86.79	86.79	
S-W F statistic (main effect)	226.44	226.44	
S-W F statistic (interaction)	173.40	173.40	
# Clusters	1,246	1,246	1,246
# Observations	463,901	463,901	463,901
Grid cell FE	X	X	X
Country-year FE	X	X	X

*** p<0.01, ** p<0.05, * p<0.1. Bilateral exports are instrumented with a variable defined as the product of the annual average global oil price and the shortest distance across the relevant land border between two cities with at least 500,000 inhabitants (adapted from Egger *et al.*, 2019). Two-way clustered standard errors at grid cell and region-year level in parentheses.
For column 3, standard errors are cluster bootstraped.

Table A15: Baseline specifications with imports as trade variable

Dependent variable: Light intensity (Y_{it})	(1) Logs: $\ln(Y_{it}+1)$ OLS	(2) IV	(3) Levels: Y_{it} Poisson	(4) Poisson IV	(5) Logs: $\ln(Y_{it}+1)$ OLS	(6) IV	(7) Levels: Y_{it} Poisson	(8) Poisson IV
Panel A: On-road grid cells only								
Bilateral imports (in logs)					0.001	-0.073*	0.013	0.015
					(0.005)	(0.040)	(0.013)	(0.019)
Bilateral imports (in logs) × Distance from border (in 100km)	-0.004*	0.005	-0.013***	-0.014**	-0.005**	0.002	-0.014***	-0.017**
	(0.002)	(0.009)	(0.004)	(0.006)	(0.002)	(0.009)	(0.004)	(0.007)
K-P F statistic		217.71				4.10		
S-W F statistic (main effect)						37.06		
S-W F statistic (interaction)		217.71				232.92		
# Clusters	3,867	3,867	3,867	3,867	3,867	3,867	3,867	3,867
# Observations	400,292	400,292	400,292	400,292	400,292	400,292	400,292	400,292
Panel B: Off-road grid cells only								
Bilateral imports (in logs)					0.003*	-0.030**	0.027**	0.040**
					(0.002)	(0.014)	(0.013)	(0.020)
Bilateral imports (in logs) × Distance from border (in 100km)	-0.002*	0.003	-0.012**	-0.016**	-0.002*	0.003	-0.013**	-0.017**
	(0.001)	(0.004)	(0.005)	(0.007)	(0.001)	(0.004)	(0.006)	(0.007)
K-P F statistic		112.45				4.61		
S-W F statistic (main effect)						119.05		
S-W F statistic (interaction)		112.45				129.51		
# Clusters	3,716	3,716	3,709	3,709	3,721	3,721	3,714	3,714
# Observations	616,136	616,136	615,112	615,112	616,142	616,142	615,160	615,160
Panel C: On-road + off-road grid cells								
Bilateral imports (in logs)					0.001	-0.050**	0.010	0.019
					(0.003)	(0.022)	(0.013)	(0.019)
Bilateral imports (in logs) × Distance from border (in 100km)	-0.001	0.010	-0.008	-0.012*	-0.001	0.008	-0.009*	-0.013*
	(0.002)	(0.008)	(0.005)	(0.007)	(0.002)	(0.008)	(0.005)	(0.007)
K-P F statistic		158.59				4.32		
S-W F statistic (main effect)						146.60		
S-W F statistic (interaction)		158.59				176.72		
# Clusters	4,122	4,122	4,122	4,122	4,125	4,125	4,125	4,125
# Observations	1,016,430	1,016,430	1,016,430	1,016,430	1,016,434	1,016,434	1,016,434	1,016,434
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

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

Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

Table A16: Effects by continent

Dependent variable: Light intensity: Y_{it}	(1) Africa Poisson IV	(2) Asia Poisson IV	(3) Europe Poisson IV	(4) Latin America Poisson IV	(5) North America Poisson IV	(6) Africa Poisson IV	(7) Asia Poisson IV	(8) Europe Poisson IV	(9) Latin America Poisson IV	(10) North America Poisson IV
Panel A: On-road grid cells only										
Bilateral exports (in logs)						0.013	0.098	-0.022	-0.065	0.616***
						(0.046)	(0.076)	(0.054)	(0.151)	(0.181)
Bilateral exports (in logs) × Distance from border (in 100km)	0.012	-0.023**	-0.034	0.009	-0.023	0.011	-0.024**	-0.030	0.013	-0.023
	(0.011)	(0.011)	(0.025)	(0.034)	(0.021)	(0.012)	(0.012)	(0.024)	(0.033)	(0.020)
# Clusters	849	1,015	1,322	349	100	849	1,015	1,322	349	100
# Observations	52,350	99,080	100,772	43,037	60,425	52,350	99,080	100,772	43,037	60,425
Panel B: Off-road grid cells only										
Bilateral exports (in logs)						0.049	0.111**	0.066	0.003	1.080***
						(0.037)	(0.048)	(0.113)	(0.217)	(0.406)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.002	-0.023*	-0.126**	-0.006	-0.221***	-0.003	-0.014	-0.119**	-0.024	-0.235***
	(0.004)	(0.013)	(0.062)	(0.054)	(0.056)	(0.005)	(0.015)	(0.058)	(0.055)	(0.043)
# Clusters	876	1,005	1,110	352	110	876	1,005	1,110	353	110
# Observations	115,780	202,351	59,926	112,271	91,335	115,780	202,351	59,926	112,274	91,335
Panel C: On-road + off-road grid cells										
Bilateral exports (in logs)						0.027	0.095*	0.016	-0.103	0.724**
						(0.041)	(0.053)	(0.063)	(0.155)	(0.290)
Bilateral exports (in logs) × Distance from border (in 100km)	0.008	-0.027**	-0.072*	0.025	-0.078**	0.006	-0.024**	-0.067*	0.030	-0.079**
	(0.008)	(0.011)	(0.037)	(0.053)	(0.033)	(0.008)	(0.012)	(0.035)	(0.053)	(0.034)
# Clusters	938	1,076	1,378	369	110	938	1,076	1,378	370	110
# Observations	168,130	301,431	160,978	155,308	151,760	168,130	301,431	160,978	155,311	151,760
Grid cell FE	X	X	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X	X					
Country-year FE						X	X	X	X	X

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

Two-way clustered and bootstraped standard errors at grid cell and region-year level in parentheses.

Table A17: Urban vs. rural roads in levels (500k)

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) OLS	(2) IV	(3) OLS	(4) IV
Bilateral exports (in logs)			0.378^{***}	0.119
			(0.089)	(1.048)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.099^{***}	-0.224^{***}	-0.087^{***}	-0.161^{**}
	(0.026)	(0.066)	(0.024)	(0.079)
Urban road (dummy) × Bilateral exports (in logs)	-0.201^{**}	-0.374^{***}	-0.200^{**}	-0.410^{**}
	(0.078)	(0.138)	(0.079)	(0.179)
Urban road (dummy) × Distance from border × Bil. exports	0.090	0.144	0.091	0.156
	(0.077)	(0.126)	(0.078)	(0.140)
K-P F statistic		15.22		2.95
S-W F statistic (main effect)				26.27
S-W F statistic (Exp x Dist interaction)		80.46		94.32
S-W F statistic (Exp x Urb interaction)		60.14		81.31
S-W F statistic (triple interaction)		107.30		124.56
# Clusters	3,633	3,633	3,633	3,633
# Observations	354,885	354,885	354,885	354,885
Grid cell FE	X	X	X	X
Country-pair-year FE	X	X		
Country-year FE			X	X

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

On-road grid cells only. Two-way clustered standard errors at grid cell and region-year level in parentheses.

Table A18: Urban vs. rural roads (100k)

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Logs: $\ln(Y_{it}+1)$ OLS	(2) Logs: $\ln(Y_{it}+1)$ IV	(3) Levels: Y_{it} Poisson	(4) Levels: Y_{it} Poisson IV	(5) Logs: $\ln(Y_{it}+1)$ OLS	(6) Logs: $\ln(Y_{it}+1)$ IV	(7) Levels: Y_{it} Poisson	(8) Levels: Y_{it} Poisson IV
Bilateral exports (in logs)					0.063^{***}	0.307^{**}	0.101^{***}	0.104^{***}
					(0.012)	(0.135)	(0.025)	(0.035)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.021^{***}	-0.040^{***}	-0.021^{***}	-0.022^{***}	-0.019^{***}	-0.052^{***}	-0.019^{***}	-0.019^{**}
	(0.004)	(0.012)	(0.005)	(0.008)	(0.004)	(0.014)	(0.006)	(0.008)
Urban road (dummy) × Bilateral exports (in logs)	-0.021^{***}	-0.064^{**}	-0.025^{**}	-0.027^{*}	-0.021^{**}	-0.079^{***}	-0.020	-0.016
	(0.007)	(0.025)	(0.011)	(0.015)	(0.009)	(0.025)	(0.014)	(0.021)
Urban road (dummy) × Distance from border × Bil. exports	-0.005	-0.018	-0.006	-0.004	-0.003	0.003	-0.007	-0.007
	(0.007)	(0.025)	(0.010)	(0.014)	(0.007)	(0.029)	(0.010)	(0.015)
K-P F statistic		23.33				2.97		
S-W F statistic (main effect)						28.07		
S-W F statistic (Exp x Dist interaction)		76.65				92.91		
S-W F statistic (Exp x Urb interaction)		88.54				111.19		
S-W F statistic (triple interaction)		97.36				126.71		
# Clusters	3,626	3,626	3,626	3,626	3,626	3,626	3,626	3,626
# Observations	353,831	353,831	353,831	353,831	353,831	353,831	353,831	353,831
Grid cell FE	X	X	X	X	X	X	X	X
Country-pair-year FE	X	X	X	X				
Country-year FE					X	X	X	X

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

On-road grid cells only. Urban road defined as road that leads to a city with at least 100,000 inhabitants.

Two-way clustered standard errors at grid cell and region-year level in parentheses. For columns 4 and 8, standard errors are cluster bootstraped.

Table A19: Summary statistics: crops

Crop	Mean weight (percent)
Barley	2.35
Cotton	0.28
Maize	2.76
Oilpalm	0.07
Rice	2.86
Rye	0.57
Sorghum	0.33
Soybean	0.91
Sunflower	0.73
Wheat	6.27

Data from Monfreda *et al.* (2008)