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 2,061 border-crossing roads in 146 countries. We observe a significant 'border shadow': on average, lights are 18 percent dimmer within 30 kilometers of the border than further inland. We find this difference to be reduced by trade expansion as measured by exports and instrumented with tariffs on the opposite side of the border. In our baseline estimate, a doubling of exports to a particular neighbor country increases night lights by 18.5 percent at the border but only by 12.9 percent 200 kilometers inland. We provide evidence that local export-oriented production is a significant mechanism behind the observed effects. Through the lens of theory, 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 30 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 typically run through naturally inhospitable regions such as mountain ranges or deserts. 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 geography models. However, when agglomeration forces are strong enough, trade liberalization can benefit interior regions disproportionately in a large class of 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 doubling of exports to a particular neighbor country increases night lights by 18.5 percent at the border but only by 12.9 percent 200 kilometers inland.

Our analysis should also interest policy makers. The relative underdevelopment of border regions is a regularity observed in countries across all levels of income. The stakes are likely to be highest, however, 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.[2] 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 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 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

[1]See Table 2.

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

exports between the two countries separated by a border, reduces the intensity of the border shadow. This effect is robust to location fixed effects and to the inclusion of an array of controls, and it seems to be driven at least in part by local export-oriented production.

Our empirical specification is grounded in theory. We start from a spatial model with a potentially rich geography (Allen and Arkolakis, 2014) and show in Section 2 that a border shadow can emerge for two distinct reasons. First, exogenous given features such as productivity or amenities can be different 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 has implications for equilibrium stability in a large class of models.

Our analysis builds on 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).[3] 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.[4] We study this issue explicitly in Section 2, based on the seminal model of Allen and Arkolakis (2014).

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 as-

[3]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). Both of those modeling approaches are compatible with trade liberalization either increasing or decreasing economic activity in border regions. In urban-systems models, this essentially depends on whether border regions are specialized in comparative-advantage or comparative-disadvantage sectors; whereas in new economic geography settings it is assumptions on the size of regions and strength of agglomeration economies that determine whether cross-border liberalization will end up drawing activity toward the border or pushing it further inland. These theories therefore do not offer any clear predictions on the impact of trade liberalization on the economic development of border regions.

[4]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. In simpler three-region economic geography models, trade triggers agglomeration in national interiors when it leads to dispersion forces falling more strongly than concentration forces (e.g. Monfort and Nicolini, 2000; Crozet and Koenig Soubeyran, 2004). Moreover, effects may be heterogeneous across different border regions. Redding (2016) and Redding and Rossi-Hansberg (2017) simulate multi-location models with rich geographies in which falling trade costs generate additional activity in some border regions but not in others.

sociated with the spatial dispersion of activities within countries.[5] 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).[6]

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 trade liberalization disproportionately favoring the economic development of border regions.

In this paper we offer three main extensions to this existing body of research. First, we extend the analysis to essentially the entire world economy, allowing us in particular to explore border-region trade effects in developing countries.[7] 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 empirical results, and Section 6 concludes.

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

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

[7] 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.

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.[8]

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 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:

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

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.[9] It is apparent from equation (1) that if $\gamma_1 > 0$, output might be lower close to the border if the exogenous productivities and amenities 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:

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

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, 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:

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

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

[9] 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.

where X_{i,C_2} are the total flows from i to locations in country 2 and $\gamma_2 = 1 - \beta + \alpha\sigma + \beta\sigma$. This equation can be rewritten as an infinite sum that converges if $|\gamma_2/\gamma_1| < 1$:[10]

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

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:

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

so that the share of exports in output is negatively correlated with the distance to the border.[11] Going back to equation (2), we find that

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

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:

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

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 baseline empirical specification (see equation 6 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

[10]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.

[11]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 $|\gamma_2/\gamma_1| > 1$.

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 displays a case where $\gamma_1 > 0$ (using the baseline parameter values from Allen and Arkolakis, 2014). In this case, equilibrium output is lower closer to the border, and the elasticity of output with respect to the border cost is more negative for locations close to the border – consistent with a border shadow that is exacerbated by high trade costs. The right panel 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.[12] 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.

3 Data

3.1 Construction of the dataset

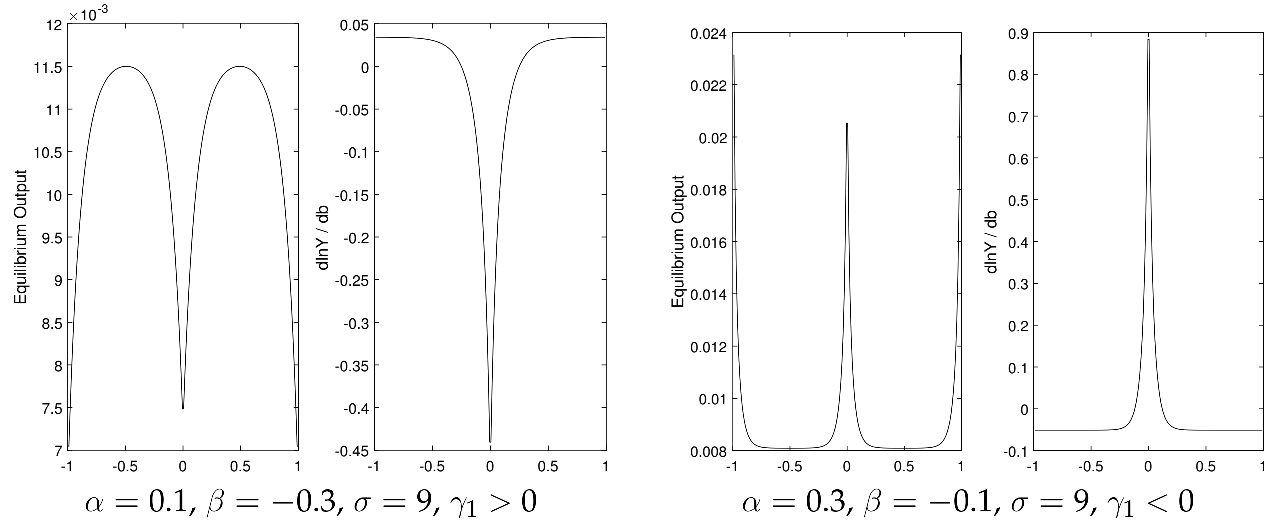
The uses and limitations of *night lights* data as a proxy for economic activity have been widely discussed.[13] Night lights have been found to represent a reliable proxy for economic activity at the sub-national level. Bruederle and Hodler (2018), for instance, document how night lights correlate positively 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 clearly positive but rather noisy, a parabolic regression 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.[14] 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

[12]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.

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

[14]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.

Figure 1: 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. 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.

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.[15] 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 model we consider.

We use the 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 200 kilometers of international land borders. Distance from the border is measured along *road corridors*.[16] We consider all border-crossing roads according to the 2011 version of the ESRI World Roads dataset (see Figure 2).[17] Our analysis is thus based on 2,061 border crossings. As shown in Table 1, we observe 30 land border crossings in the average advanced economy but only 19 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 62% of border crossings observed in our data.

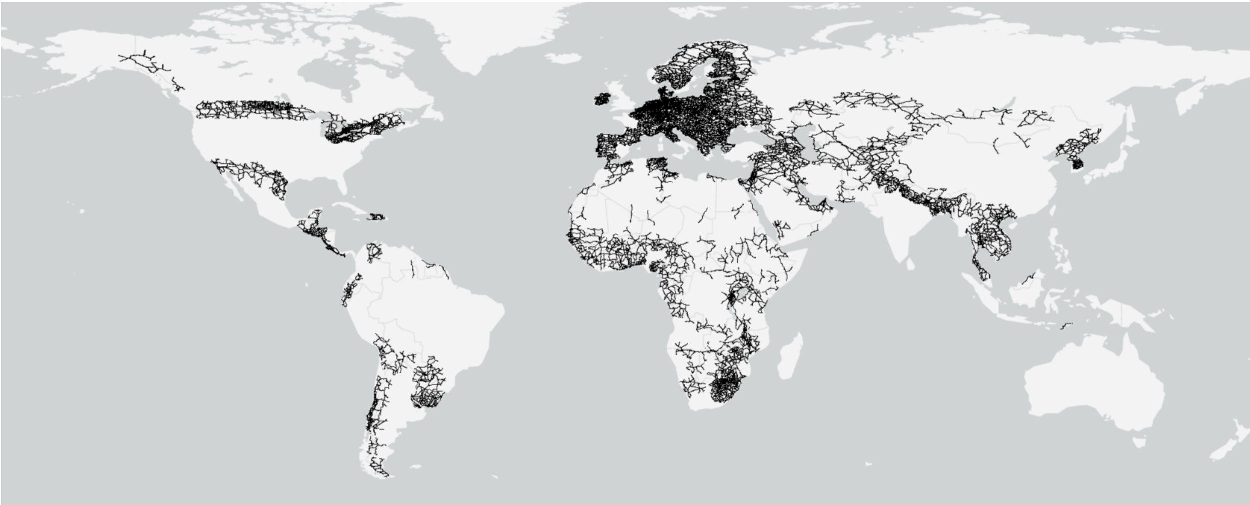
Based on our sample of border-crossing roads, we perform a number of operations on the raw lights data using GIS software. An illustration is given in Figure 3. Panel (a) shows our

[15]See Appendix Table A1.

[16]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.

[17]The identification of roads is based on information provided by national authorities. Since all 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 200km from the border, as defined in the 2011 ESRI World Roads dataset.

Table 1: Borders and border crossings

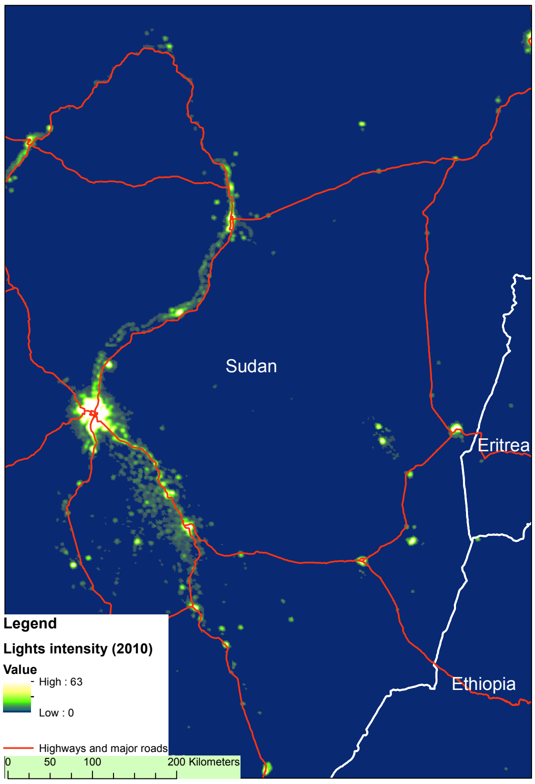
	Land borders per country	Border crossings per country	Border crossings per border	Total number of border crossings	Total number of grid cells
Advanced economies (40)	3.53	30.07	8.53	793	175,959
Developing economies (114)	3.92	19.49	4.97	1,268	437,682

Note: Countries grouped according to 2015 World Bank classification.

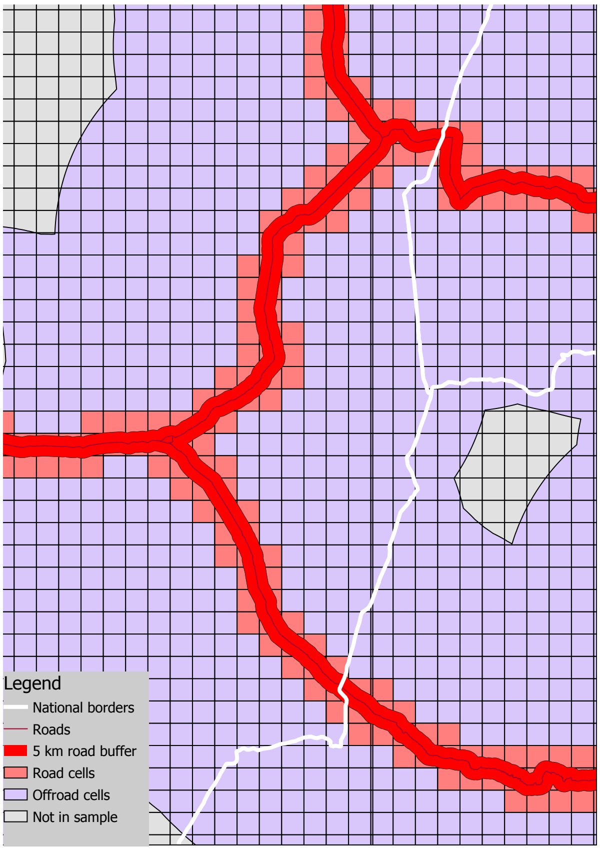
sample roads in the case of the border region between Sudan, Eritrea and Ethiopia. To be part of our analysis, a road needs to cross a land border and be classified as a "highway", "major road" or "local road" in the ESRI dataset. The figure illustrates how lights cluster along such road corridors. Panel (a) 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

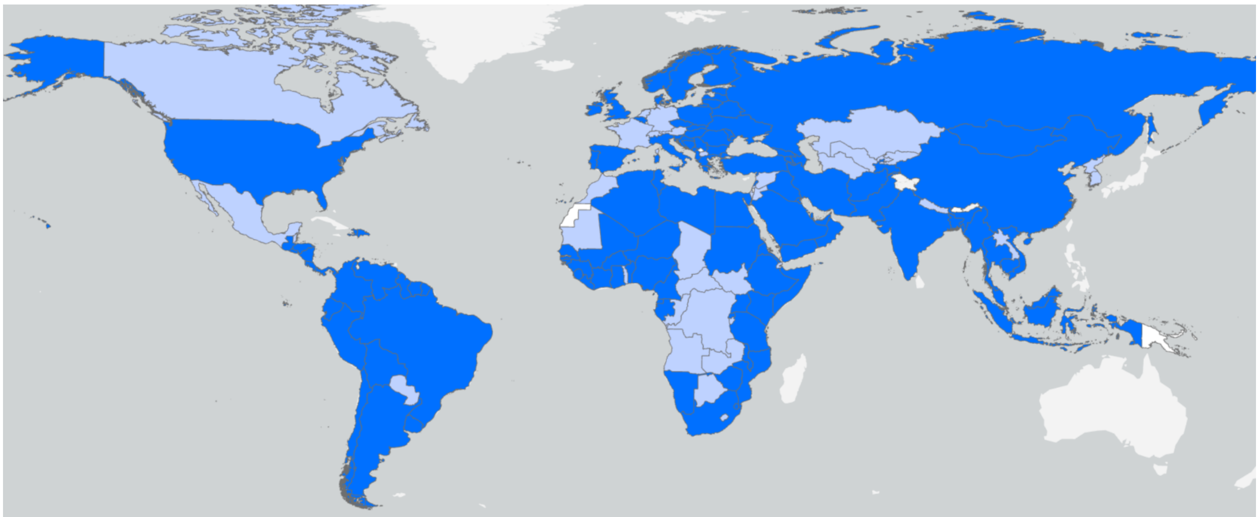


Note: National borders in white, major roads in red. Grid cells illustrated in panel (b) enter the baseline sample (on-road + off-road) if their road distance from the closest border is <= 200 kilometers and their geodesic distance from the closest road is <= 100 kilometers. Source: ESRI ArcGIS.

In panel (b) of Figure 3, we zoom in further to illustrate the construction of our units of observation. Our basic units are 10 × 10 kilometer grid cells. In order to be part of our sample, a grid cell needs to be within 200 kilometers along the road from the border. Within each of these cells, we compute the average light intensity of all 1 × 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 236,000 on-road and 373,000 off-road grid cells for each of the years 1995, 2000, 2005, 2010 and 2013.[18] For each on-road

[18]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

Figure 4: Dark land border regions dominate



Note: Sample countries are displayed according to the average light intensities along road corridors 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 30 kilometers, are on average darker than interior and coastal regions, and vice-versa for light blue countries.

cell, we compute the distance of its center from the closest border along the border-crossing road, as well as the geodesic distance from the nearest sea port and airport. For each 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.[19]

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

3.2 The border shadow

Importantly for the purpose of this paper, border shadows can easily be documented in the raw data.

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 30 kilometers of land borders (the "border region") and for grid cells located further inland.[20] 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: 76% of mapped countries feature relatively "dark" border regions (111 of the 146 countries shown in Figure 4). Weighted by population, these account for 90% of the sample, and weighted by GDP, they account for 87% of the sample.

As shown in Table 2, border-region road corridors are some 18% darker, averaged across countries, than those road corridors beyond 30 kilometers from the border. This difference is statistically significant.

Nordhaus, 2015), we limit our baseline panel to the period from 1995 to 2013.

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

[20]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 (0-30km from border)	4.34	4.87		146
Interior region (>30 km from border)	5.32	5.71		146
Difference	-0.98		-4.32	

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

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, theory 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.[21] 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.

4.1 Empirical models

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 $y_{it} = \ln(Y_{it})$, (a) we also estimate linear specifications with lights measured in levels, (b) we add 1 to recorded lights before taking logs, and (c) we estimate Poisson models on lights measured in levels. Roads r are defined as belonging to one country only, such that every cross-border road 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

[21]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).

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:

$$y_{it} = \ln(Y_{it}) = \beta_0 + \beta_1 T_{cc't} + \beta_2 (d_i^{border} \times T_{cc't}) + \gamma_i + \gamma_{ct} + u_{it}, \quad (6)$$

where γ_i denotes 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-year fixed effects γ_{ct} to filter out country-level changes in luminosity.[22] In this specification, β_1 captures the effect on night lights of increased cross-border trade at the border crossing (where $d_i^{border} = 0$). Our parameter of main interest is the interaction term β_2, which 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 an alternative specification, we replace grid-cell fixed effects by cross-sectional controls for exogenous or predetermined sources of spatial heterogeneity, and we in addition consider distance from the nearest border-crossing road of off-road locations. The empirical model then becomes:

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 d_i^{border} + \beta_2 T_{cc't} + \beta_3 (d_i^{border} \times T_{cc't}) \\ + \beta_4 (d_i^{road}) + \beta_5 (d_i^{road} \times T_{cc't}) + \theta \mathbf{x}_i + \gamma_r + \gamma_{ct} + w_{it}, \quad (7) \end{aligned}$$

where $\mathbf{x}_i$ is a vector of grid-cell-level controls that includes average altitude, average slope, dummy variables for whether a sea port or airport respectively is closer to i than the nearest land border, and interactions of those two dummies with the geodesic distance from the port or airport in question. Road fixed effects, γ_r soak up any unobserved time-invariant specificities of particular roads affecting their average luminosity, such as the quality and capacity of the road. In this specification, we moreover include d_i^{road}, the geodesic distance of cell i to the nearest grid cell on a border-crossing road r (hence, $d_i^{road} = 0 \Leftrightarrow \mathit{Off}_i = 0$, where Off_i is a dummy variable that takes the value of 1 if sample grid cell i is not within 5 kilometers of a border-crossing road).

The regression specification without grid-cell fixed effects allows us to estimate border shadows: a significantly positive estimate of β_1 in equation (7) is evidence for the border shadow at zero trade, as it implies that economic activity increases as one moves inland, away from the border, when $T_{cc't} = 0$. When there is a border shadow, i.e. β_1 is positive, then a negative estimate of β_3 implies an attenuation of the border shadow with a stronger increase in economic activity at locations closer to the border.

4.2 Identification and inference

As we seek to capture the causal effect of changed trade intensities on the geography of night lights, 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 and country-year fixed effects mitigate much of this concern.

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

Nonetheless, we also estimate equations (6) and (7) by instrumenting bilateral exports $T_{cc't}$ with tariffs imposed by destination country c' on goods from origin country c. Since trade weights could also be endogenous, tariffs are computed as unweighted averages across sectors.[23] We analogously instrument the interaction term $(d_i^{border} \times T_{cc't})$ with the product of distance and neighbor-country tariffs.

Our identifying assumption is that activity in grid cell i does not directly affect tariffs imposed by neighbor country c'. Given the small size of our cells and the inclusion of region-year fixed effects, this assumption strikes us as unproblematic. The exclusion restriction we impose requires that, conditional on fixed effects, tariffs of country c' affect economic activity in country c only through the volume of exports from c to c'. We consider this to be a similarly 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. [24]

Throughout the analysis, we cluster standard errors two ways. For estimations of specification (6), we cluster by grid cell i and by region-year st or 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. For estimations of specification (7), we cluster by road r and by country-pair-year $cc't$. Roads represent the main dimension of the fixed effects structure in regression model (7), and country-pair-year is the dimension of variation of our trade variable.

5 Results

5.1 Baseline estimates: How exports affect light gradients

Table 3 presents our baseline estimates taking exports as the trade measure. Panel A shows estimates based on on-road grid cells only (equation 6), panel B shows corresponding estimates for off-road grid cells only, and Panel C shows estimates for both sub-samples combined. For all three samples, we estimate linear specifications with the dependent variable in levels and in logs, without and with instrumenting exports, and with a Poisson estimator.

Our coefficient estimates turn out to be stable across specifications, statistically significant in most instances, and consistent with attenuated light gradients throughout. OLS and IV estimates are qualitatively identical. The first-stage F-statistics are mixed: K-P statistics are relatively low, but S-W statistics are higher, especially for our main coefficient of interest on the interaction term. Instrumenting increases the estimated main effect of exports, $\hat{\beta}_2$. This could reflect the effect of measurement error on trade volumes biasing these estimates towards zero in the OLS estimations.

Our baseline estimates of the main effect of increased exports, $\hat{\beta}_1$ of equation (6), are always positive and mostly statistically significant. Hence, increased bilateral exports are found to be associated with increased light intensity at the relevant land border (i.e. where $d_i^{border} = 0$). Our coefficient of main interest, the interaction term on trade changes and

[23]We also use year-t imports of country c' from countries other than c as an alternative instrument.

[24]The limitation of K-P F-statistics in our context is that no critical values exist for the case of 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 heterogeneity. We follow the recent practice of reporting both measures.

Table 3: Baseline estimates

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1) Levels: Y_{it} OLS	(2) Levels: Y_{it} IV	(3) Logs: $\ln(Y_{it}+1)$ OLS	(4) Logs: $\ln(Y_{it}+1)$ IV	(5) Levels: Y_{it} Poisson
Panel A: On-road grid cells only					
Bilateral exports (in logs)	0.076***	0.575	0.016***	0.245**	0.029***
	(0.022)	(0.712)	(0.003)	(0.108)	(0.006)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.038***	-0.147***	-0.010***	-0.035***	-0.017***
	(0.013)	(0.056)	(0.002)	(0.010)	(0.003)
K-P F statistic		4.50		4.50	
S-W F statistic (main effect)		11.54		11.54	
S-W F statistic (interaction)		138.69		138.69	
# Clusters	9,229	8,361	9,229	8,361	9,229
# Observations	961,696	869,463	961,696	869,463	961,696
Panel B: Off-road grid cells only					
Bilateral exports (in logs)	0.028***	0.239	0.010***	0.118	0.048***
	(0.007)	(0.275)	(0.002)	(0.085)	(0.009)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.014***	-0.036***	-0.004***	-0.011***	-0.022***
	(0.004)	(0.014)	(0.001)	(0.004)	(0.005)
K-P F statistic		1.12		1.12	
S-W F statistic (main effect)		2.36		2.36	
S-W F statistic (interaction)		287.07		287.07	
# Clusters	8,815	8,043	8,815	8 ,043	8,810
# Observations	1,417,124	1,256,178	1,417,124	1,256,178	1,417,102
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	0.051***	0.313	0.013***	0.178**	0.041***
	(0.012)	(0.389)	(0.002)	(0.091)	(0.007)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.023***	-0.086***	-0.007***	-0.022***	-0.019***
	(0.007)	(0.028)	(0.001)	(0.006)	(0.004)
K-P F statistic		2.33		2.33	
S-W F statistic (main effect)		5.35		5.35	
S-W F statistic (interaction)		271.67		271.67	
# Clusters	9,814	8,957	9,814	8,957	9,814
# Observations	2,378,825	2,125,647	2,378,825	2,125,647	2,378,825
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

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

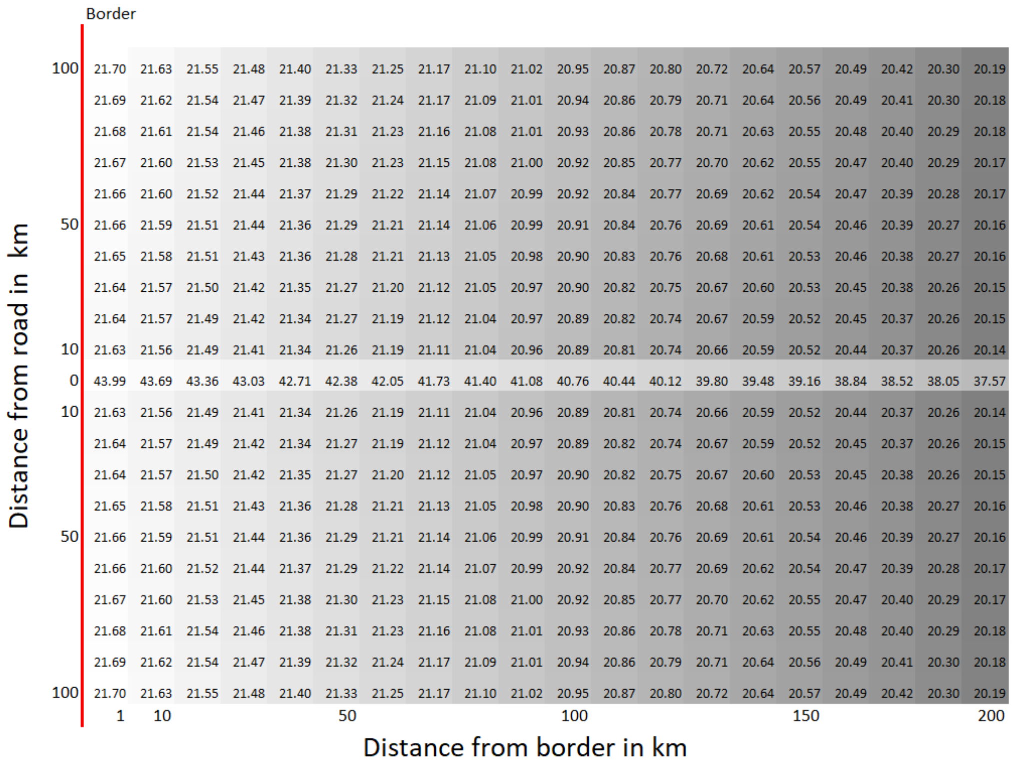
distance from the border, $\hat{\beta}_2$ of equation (6), is estimated even more precisely, with a negative sign throughout: increased bilateral exports are associated with stronger increases in night lights close to the relevant land border than further inland. For example, the estimated coefficient in the on-road sample of Table 3, column 4, implies that the brightening effect of export growth falls by some 3.5 percent with every 100 kilometers of distance from the border. Put differently, these estimates imply that a doubling of cross-border trade will increase night lights by 18.5 percent at the border crossing but only by 12.9 percent 200 kilometers inland.

We explore the robustness of those baseline estimates. First, 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.[25] Second, we drop small countries from the estimation sample. Again, our baseline estimates remain essentially unchanged.[26] Third, we apply country-year level error clustering instead

[25] See Appendix Table A5.

[26] See Appendix Table A6.

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 value of the 25th percentile in our data, based on separate regressions for on-road and off-road grid cells, with road and country-year fixed effects, all control variables, and exports instrumented with tariffs. Darker colors symbolize lower light intensity.

of our baseline region-year level clustering. This reduces the number of clusters by an order of magnitude, but all our estimated interaction effects remain statistically significant.[27] Fourth, we investige our IV strategy. Reduced-form estimates yield the expected results: higher tariffs are associated with lower night lights at the border and significantly more positive gradients with respect to distance from the border.[28] In a complementary exercise, we take year-t imports of country c' from all other countries except c as an alternative, 'shift-share-type', instrument. Our qualitative finding obtains also with this approach.[29]

In Table 4, we report regression estimates of equation (7), which does not include grid-cell fixed effects and therefore allows us to estimate static border shadows (as well as offering a 'sanity check' on the baseline estimates). Our main findings of Table 3 carry over: increased bilateral exports are associated with brighter night lights in the respective border regions, and this increase in lights is more pronounced close to the border than further inland. In addition, we find evidence of border shadows in levels: estimated coefficients on the raw distance measure, $\hat{\beta}_1$ of equation (7), are significantly positive across all specifications. According to the IV estimate shown in column (4) of Table 4, economic activity measured through

[27]See Appendix Table A7.

[28]See Appendix Table A8.

[29]See Appendix Table A9. Unsurprisingly, this instrument is considerably more strongly correlated with bilateral trade flows and thus yields higher first-stage F-statistics, but it also is less plausibly exogenous than our preferred instrument, neighbor-country import tariffs.

night lights is some 19 percent higher 100 kilometers inland than at the border crossing, in a hypothetical scenario of zero cross-border trade.

Table 4: Baseline effects without grid-cell fixed effects

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Light intensity (Y_{it})	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Distance from border (in 100km)	1.060***	1.910**	0.097***	0.190*	0.255**
	(0.391)	(0.741)	(0.037)	(0.109)	(0.108)
Distance from road (in 100km)	6.302***	5.990***	0.667***	0.283	1.981***
	(1.332)	(2.239)	(0.181)	(0.372)	(0.702)
Bilateral exports (in logs)	0.189***	0.505	0.023***	0.177	0.057***
	(0.038)	(0.432)	(0.005)	(0.154)	(0.013)
Bilateral exports × Distance from border	-0.058***	-0.099***	-0.005***	-0.010*	-0.012**
	(0.021)	(0.037)	(0.002)	(0.005)	(0.005)
Bilateral exports × Distance from road	-0.411***	-0.389***	-0.050***	-0.030	-0.158***
	(0.072)	(0.114)	(0.010)	(0.019)	(0.038)
Altitude (in 100m)	-0.094***	-0.091***	-0.014***	-0.013***	-0.044***
	(0.015)	(0.016)	(0.002)	(0.002)	(0.006)
Slope	-0.084***	-0.087***	-0.009***	-0.009***	-0.009
	(0.022)	(0.022)	(0.003)	(0.003)	(0.007)
Port closer than next land border (dummy)	2.924***	2.979***	0.302***	0.312***	0.390***
	(0.418)	(0.438)	(0.039)	(0.041)	(0.067)
Distance from port (in 100km)	-0.006	0.023	-0.005	-0.001	-0.013
	(0.055)	(0.057)	(0.007)	(0.007)	(0.021)
Port dummy × Distance from port	-2.325***	-2.354***	-0.224***	-0.231***	-0.314***
	(0.322)	(0.335)	(0.030)	(0.032)	(0.056)
Airport closer than next land border (dummy)	4.304***	4.310***	0.392***	0.385***	0.595***
	(0.327)	(0.353)	(0.027)	(0.028)	(0.041)
Distance from airport (in 100km)	-0.420***	-0.452***	-0.049***	-0.052***	-0.193***
	(0.063)	(0.068)	(0.007)	(0.008)	(0.023)
Airport dummy × Distance from airport	-3.534***	-3.553***	-0.316***	-0.310***	-0.600***
	(0.279)	(0.299)	(0.022)	(0.023)	(0.039)
K-P F statistic		0.47		0.47	
S-W F statistic (main effect)		1.61		1.61	
S-W F statistic (interaction: Distance from border)		40.13		40.13	
S-W F statistic (interaction: Distance from road)		24.26		24.26	
# Clusters	1,210	1,084	1,210	1,084	1,210
# Observations	2,410,626	2,155,085	2,410,626	2,155,085	2,410,626
Road FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

Two-way clustered standard errors at road and country pair-year level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Sample contains all border-region grid cells (on-road + off-road).

The multiple interaction terms of our complete regression specification (7) do not lend themselves individually to easy interpretation. In Figure 5, we therefore illustrate changes in border-region night lights implied by a model akin to specification (4) of Table 4 preferred estimates, based on separate regressions for on-road and off-road grid cells. We show a hypothetical 200 × 200 kilometer area with an international border at its western edge and a perpendicular border-crossing road running through the middle. In this grid, we report predicted percentage changes in light intensities for a 10% increase of exports, starting from the 25th percentile value. Variation across grid cells in lights growth is determined by the estimated parameters $\hat{\beta}_1$ to $\hat{\beta}_5$ of equation (7).[30] 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 furthermore bring about the strongest growth in lights on and close to the main road corridors.[31]

In summary, we find increased trade to attract activity towards border regions, both on and off the border-crossing roads. Our estimates also imply that, within our sample distance band of 200 kilometers exports, are associated with increases in lights for all grid cells including those furthest removed from the border and the main road.[32]

5.2 Lights per capita

Table 5: Baseline effects for light intensity per capita and population

	(1)	(2)	(3)	(4)
Dependent variable:	Lights per capita (logs)		Population (logs)	
	OLS	IV	OLS	IV
Bilateral exports (in logs)	0.006**	0.045*	0.000	0.016
	(0.002)	(0.026)	(0.004)	(0.051)
Bilateral exports × Distance from border (in 100km)	-0.001	-0.002	-0.005***	-0.015***
	(0.001)	(0.001)	(0.002)	(0.006)
K-P F statistic		1.84		1.85
S-W F statistic (main effect)		5.12		5.15
S-W F statistic (interaction)		543.30		524.81
# Clusters	7,676	7,312	7,676	7,312
# Observations	789,372	736,618	792,989	740,199
Grid cell FE	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES

On-road grid cells only (see Appendix Table A10 for results including off-road locations). *** p <0.01, ** p <0.05, * p <0.1
Two-way clustered standard errors at grid cell and region-year level in parentheses.

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 is that we cannot distinguish between population and income effects: do brighter lights associated with intensified 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 the expected coefficient

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

[31]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 magnitude bigger along cross-border road corridors than at locations further removed from those roads.

[32]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.

signs are the same 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 grided population data from WorldPop, which are available at the same 10 × 10 kilometer resolution as the one we choose for our analyses based on lights only (see Appendix B for details).

In Table 5, we show estimates of our baseline specification (6) with lights per capita and population as the dependent variable. The disaggregated estimates suggest that reduced border shadows through expanded exports reflect both higher income (proxied by lights) and higher population density in border regions. The estimates shown in Table 5 suggest that the per-capita effects are evenly spread across the 200-kilometer border regions, whereas the changing distance gradient is mainly driven by population movements.

5.3 Imports

Up to now, we have defined trade $T_{cc't}$ as the value of exports from country c to country c', instrumented with the tariff rate of country c' on goods from country c. We can deploy this framework to study the effect of imports, by redefining T_{ct} as imports. Accordingly, T_{ct} is instrumented with country-c unweighted tariffs on products from the neighboring country c'.[33] Results are reported in Table 6.

Not surprisingly, we find that the both the effect of trade on economic activity at the border ($\hat{\beta}_1$ of equation 6) and the effect on the gradient from the border ($\hat{\beta}_2$ of equation 6) are somewhat less stable and less precisely estimated for imports than for exports. Overall, however, the liberalization of imports appears to be associated with comparable effects on the economic geography of border regions to the liberalization of exports.

Table 6: Imports

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Light intensity (Y_{it})	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Bilateral imports (in logs)	0.064***	-0.524	0.015***	-0.314	0.035***
	(0.017)	(0.538)	(0.003)	(0.197)	(0.005)
Bilateral imports × Distance from border (in 100km)	-0.040***	-0.042	-0.010***	-0.025***	-0.021***
	(0.010)	(0.043)	(0.002)	(0.009)	(0.003)
K-P F statistic		1.71		1.71	
S-W F statistic (main effect)		4.23		4.23	
S-W F statistic (interaction)		550.20		550.20	
# Clusters	9,207	8,480	9,207	8,480	9,207
# Observations	970,969	909,139	970,969	909,139	970,969
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

On-road grid cells only (see Appendix Table A11 for results including off-road locations). *** p <0.01, ** p <0.05, * p <0.1
Two-way clustered standard errors at grid cell and region-year level in parentheses.

[33] 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. This is the main reason why we primarily focus on exports.

5.4 Effects by world region

We now 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 individual continents.

Table 7 reports estimates of our baseline model (6) separately for developing and advanced economies, using an interaction specification with a binary variable that is set to one for advanced 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 40 advanced and 114 developing economies.

Table 7: Developing and advanced economies

Dependent variable: Light intensity (Y_{it})	(1) Levels: Y_{it} OLS	(2) IV	(3) Logs: $\ln(Y_{it}+1)$ OLS	(4) IV	(5) Levels: Y_{it} Poisson
Bilateral exports (in logs)	0.081***	0.778**	0.016***	0.118	0.038***
	(0.020)	(0.363)	(0.003)	(0.072)	(0.007)
Bilateral exports × Distance from border (in 100km)	-0.040***	-0.114**	-0.009***	-0.018*	-0.021***
	(0.011)	(0.044)	(0.002)	(0.009)	(0.004)
Advanced economy (dummy) × Bilateral exports	-0.046	-1.468	-0.011	0.865	-0.035**
	(0.113)	(4.950)	(0.016)	(0.564)	(0.015)
Advanced economy × Distance from border × Bilateral exports	0.011	-0.366	-0.009	-0.036	0.008
	(0.067)	(0.273)	(0.010)	(0.047)	(0.008)
K-P F statistic		1.83		1.83	
S-W F statistic (triple interaction)		163.52		163.52	
# Clusters	9,229	8,361	9,229	8,361	9,229
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

On-road grid cells only (see Appendix Table A12 for results including off-road locations). *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Two-way clustered standard errors at grid cell and region-year level in parentheses.

Qualitatively, our main results hold consistently for the subset of developing countries: bilateral exports growth brightens up locations in borders regions, and all the more so the closer these locations are situated to the border. The additional interaction coefficients shown in Table 7, measuring how average effects in advanced economies diverge from those estimated for developing economies, are somewhat fragile and inconsistent. When they are statistically significant, however, coefficients on the triple interaction terms are negative throughout, implying that the border-shadow attenuating effect trade expansion might be stronger still in advanced than in developing economies.[34]

We should interpret any apparent difference with care, as the effects measured in developing economies might at least partly be due to attenuation bias from measurement error in the export variable. We do not observe informal trade, which is considerably more important in developing than in advanced economies and particluarly across land borders. Moreover, even formal trade may be recorded more accurately in the latter countries. Instrumenting with neighbor-country import tariffs likely cannot entirely solve this problem, as informal exports might to some extent be a substitute for formal exports and therefore react to tariffs in the opposite way. While cross-country differences along the income dimension should

[34]See Appendix Table A12.

therefore be interpreted with caution, our results strongly suggest that exports reduce border shadows in both advanced and developing economies.

Table 8: Effects by continent

Dependent variable: Light intensity: $\log(Y_{it} + 1)$	(1) Africa IV	(2) Asia IV	(3) Europe IV	(4) Latin America IV	(5) North America IV
Bilateral exports (in logs)	-0.012	0.176	-0.018	-0.107	0.717**
	(0.020)	(0.130)	(0.075)	(0.238)	(0.292)
Bilateral exports $\times$ Distance from border (in 100km)	-0.011**	-0.014	-0.103***	0.000	-0.199**
	(0.005)	(0.021)	(0.015)	(0.012)	(0.096)
K-P F statistic	3.46	3.54	20.40	0.39	9.38
S-W F statistic (main effect)	37.57	8.90	58.01	1.92	28.49
S-W F statistic (interaction)	192.43	49.55	868.81	173.39	23.83
# Clusters	2,083	2,031	2,824	1,339	150
# Observations	147,276	171,762	331,287	99,784	119,345
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

On-road grid cells only (see Appendix Table A13 for results including off-road locations). North America defined as United States + Canada. Two-way clustered standard errors at cell and region-year level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 8, we subdivide the world further, showing estimates of our baseline model (6) individually by continent. Negative coefficients are found on our variable of main interest, the interaction term of bilateral exports and distance from the border, in four of the five continents. Latin America stands out as yielding no statistically significant coefficient estimates in any subsample.[35] This might be related to particular topographical and economic features of that continent and could merit further investigation.

5.5 A mechanism: increased border-region production

Overall, bilateral exports appear to favor the economic development of locations close to the relevant land border. 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 are conceivable. It could be that increased activity observed near borders stems mainly from non-traded services that support trading activities, or that it is the result of redistributive policies aimed at spreading 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 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 main agricultural product for each 10 $\times$ 10 kilometer grid cell as the crop that occupies the biggest share of land.[36]

[35] See Appendix Table A13.

[36] For a list of crops in the sample, see Appendix Table A14. See Appendix B for details on the data.

Table 9: Trade in local crops

Dependent variable: Light intensity: $\log(Y_{it} + 1)$	(1)	(2)	(3)	(4)
	All crops		Top 5 crops	
	IV	IV	IV	IV
Bilateral crop exports (in logs)	0.076***		0.061***	
	(0.023)		(0.020)	
Bilateral crop exports (in logs) × Distance from border (in 100km)	-0.031***		-0.035***	
	(0.010)		(0.010)	
		Effects of overall exports		
Bilateral exports (in logs)		0.152		0.141
		(0.191)		(0.186)
Bilateral exports (in logs) × Distance from border (in 100km)		-0.005		0.004
		(0.013)		(0.014)
K-P F statistic	7.64	2.02	9.96	1.79
S-W F statistic (main effect)	16.82	4.42	16.96	3.79
S-W F statistic (interaction)	17.02	60.19	14.37	53.55
# Clusters	4,434	4,434	4,339	4,339
# Observations	440,948	440,948	388,808	388,808
Grid cell FE	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES

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

We estimate two variants of equation (7). In columns (1) and (3) of Table 9, we present estimates of equation (6) using exports of the major crop grown in cell i to neighbor country c' as the trade variable, using the tariff on this product applied by neighbor-country c' and the world price of the respective crop as instruments. We alternatively consider all 10 crops (column 1) and the top-5 (column 3) crops. In columns (2) and (4), we report specifications with the trade variable defined as overall exports instrumented with average tariffs. Columns (2) and (4) of Table 9 therefore show our baseline specification estimated over the sample for which we have information on crops by way of a benchmark for comparison with the estimates for crop-specific exports.

What we find further confirms our observation that trade causes an attenuation of border shadows, and, importantly, it suggests that the stimulation of local production is a significant mechanism behind that effect. Table 9 shows that both our estimated main effect of exports and the interaction effect with distance are noticeably more precisely estimated and, in case of the interaction term of greatest interest, larger when we focus on exports of border regions' dominant crops than when we consider overall trade.

6 Conclusion

Our estimates based on world-wide spatially disaggregated data suggest that bilateral trade expansion encourages economic development in the vicinity of land borders. Given that border regions on average are less developed than interior regions, this predominantly implies a spatially equalizing effect of international trade. The effect emerges quite consistently irrespective of how we cut the data: it applies to both developing and advanced economies, and four of the five continents. We also find evidence that border regions benefit in gross terms as well as in per-capita terms, suggesting that trade expansion boosts both populations and incomes of border regions. 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. Many borders in the developing world are, in spite of modernization efforts, still largely dysfunctional. Moreover, some are the theater of conflicts between central governments and minorities and between neighboring countries, the two being sometimes linked. Bilateral trade liberalization might therefore represent an underappreciated tool for the appeasement of such conflicts.

Our analysis suggests that trade liberalization between neighbor countries tends to promote a more balanced spatial distribution of economic activity within regions located in proximity of the affected border. Night lights, although shown elsewhere to be a reliable proxy for local output, 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.[37]

References

[1] Ades, Alberto F. and Glaeser, Edward L. (1995) "Trade and circuses: Explaining urban giants." *Quarterly Journal of Economics*, 110(1): 195–227.

[2] Allen, Treb and Arkolakis, Costas (2014) "Trade and the topography of the spatial economy." *Quarterly Journal of Economics*, 129(3): 1085–1140.

[3] Allen, Treb and Arkolakis, Costas and Takahashi, Yuta (2020) "Universal Gravity." *Journal of Political Economy*, 128(2): 393–433.

[4] Andrews, Isaiah and Stock, James H. and Sun, Liyang (2019) "Weak instruments in instrumental variables regression: Theory and practice." *Annual Review of Economics*, 11: 727–753.

[5] Atkin, David and Donaldson, Dave (2015) "Who's getting globalized? The size and implications of intra-national trade costs." *Mimeo*, MIT and Stanford.

[6] Autor, David H.; Dorn, David and Hanson, Gordon H. (2013) "The China syndrome: Local labor market effects of import competition in the United States." *American Economic Review*, 103(6): 2121–2168.

[7] Bruederle, Anna and Hodler, Roland (2018) "Nighttime lights as a proxy for human development at the local level." *PLoS One*, 13(9): e0202231.

[37] We note that while in our illustrative model welfare is equalized across locations, in prominent quantitative economic geography models featuring imperfect intra-national labor mobility, local changes in population, real wages and welfare are strongly correlated (Redding, 2016).

[8] Brülhart, Marius (2011) "The spatial effects of trade openness: A survey." *Review of World Economics*, 147(1): 59–83.

[9] Brülhart, Marius; Carrère, Céline, and Robert-Nicoud, Frédéric (2018) "Trade and towns: heterogeneous adjustment to a border shock." *Journal of Urban Economics*, 105: 162-175.

[10] Brülhart, Marius, Carrère, Céline, and Trionfetti, Federico (2012): "How wages and employment adjust to trade liberalization: Quasi-experimental evidence from Austria." *Journal of International Economics*, 86(1): 68–81.

[11] Caliendo, Lorenzo; Dvorkin, Maximiliano and Parro, Fernando (2019) "Trade and labor market dynamics: General equilibrium analysis of the China trade shock." *Econometrica*, forthcoming.

[12] Chen, Xi and Nordhaus, William (2015) "A Test of the new VIIRS lights data set: Population and economic output in Africa." *Remote Sensing*, 7(4): 4937-4947.

[13] Cosar, A. Kerem and Fajgelbaum, Pablo D. (2016) "Internal geography, international trade, and regional specialization." *American Economic Journal: Microeconomics*, 8(1): 24–56.

[14] Crozet, Matthieu and Koenig Soubeyran, Pamina (2004) "EU enlargement and the internal geography of countries." *Journal of Comparative Economics*, 32(2): 265–278.

[15] Dix-Carneiro, Rafael and Kovak, Brian K. (2017) "Trade liberalization and regional dynamics." *American Economic Review*, 107(10): 2908–2946.

[16] Donaldson, Dave and Storeygard, Adam (2016) "The view from above: Applications of satellite data in economics." *Journal of Economic Perspectives*, 3(4): 171–198.

[17] Elvidge, Christophe D.; Ziskin, Daniel; Baugh, Kimberly E.; Tuttle, Benjamin T.; Ghosh, Tilottama; Pack, Dee W.; Erwin, Edward H. and Zhizhin, Mikhail (2009) "A fifteen year record of global natural gas flaring derived from satellite data." *Energies*, 2(3): 595–622.

[18] Fajgelbaum, Pablo D. and Redding, Stephen J. (2022) "Trade, structural transformation and development: Evidence from Argentina 1869-1914." *Journal of Political Economy*, 130(5): 1249–1318.

[19] Hanson, Gordon H. (1998) "Regional adjustment to trade liberalization." *Regional Science and Urban Economics*, 28(4): 419–444.

[20] Henderson, Vernon (1982) "Systems of cities in closed and open economies." *Regional Science and Urban Economics*, 12(3), 325–350.

[21] Henderson, Vernon; Storeygard, Adam and Weil, David N. (2012) "Measuring economic growth from outer space." *American Economic Review*, 102(2): 994–1028.

[22] Hirte, Georg; Lessmann, Christian and Seidel, André (2020) "International trade, geographic heterogeneity and interregional inequality." *European Economic Review*, 127(103427).

[23] Kanbur, Ravi and Zhang, Xiaobo (2005) "Fifty years of regional inequality in China: A journey through central planning, reform, and openness." *Review of Development Economics*, 9(1): 87–106.

[24] König, Michael D.; Rohner, Dominic; Thoenig, Mathias and Zilibotti, Fabrizio (2017) "Networks in conflict: Theory and evidence from the Great War of Africa." *Econometrica*, 85(4): 1093–1132.

[25] Krugman, Paul and Livas Elizondo, Raul (1996) "Trade policy and the third world metropolis." *Journal of Development Economics*, 49(1): 137–150.

[26] Levin, Noam *et al.* (2020) "Remote sensing of night lights: A review and an outlook for the future." *Remote Sensing of Environment*, 237(111443).

[27] Michalopoulos, Stelios and Papaioannou, Elias (2016) "The long-run effects of the Scramble for Africa." *American Economic Review*, 106(7): 1802–1848.

[28] Monfort, Philippe and Nicolini, Rosella (2000) "Regional convergence and international integration." *Journal of Urban Economics*, 48(2): 286–306.

[29] Monfreda, Chad, Navin Ramankutty, and Jonathan A. Foley (2008) "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000." *Global Biogeochemical Cycles* 22: GB1022.

[30] Nagy, Dávid Krisztián (2022) "Trade and urbanization: Evidence from Hungary." *American Economic Journal: Microeconomics*, 14(3): 733–790.

[31] Pinkovskiy, Maxim L. (2017) "Growth discontinuities at borders." *Journal of Economic Growth*, 22(2): 145–192.

[32] Pinkovskiy, Maxim L. and Sala-i-Martin, Xavier (2017) "Lights, camera ... income! Illuminating the national accounts-household surveys debat." *Quarterly Journal of Economics*, 131 (2): 579-631.

[33] Rauch, James E. (1991) "Comparative advantage, geographic advantage and the volume of trade." *Economic Journal*, 101(408): 1230–1244.

[34] Redding, Stephen J. (2016) "Goods trade, factor mobility and welfare." *Journal of International Economics*, 101: 148–167.

[35] Redding, Stephen J. and Rossi-Hansberg, Esteban (2017) "Quantitative spatial economics." *Annual Review of Economics*, 9: 21–58.

[36] Redding, Stephen J. and Sturm, Daniel M. (2008) "The costs of remoteness: Evidence from German division and reunification." *American Economic Review*, 98(5): 1766–1797.

[37] Rossi-Hansberg, Esteban (2005) "A spatial theory of trade." *American Economic Review*, 95(5): 1464–1491.

[38] Storeygard, Adam (2016) "Farther on down the road: Transport costs, trade and urban growth in sub-Saharan Africa." *Review of Economic Studies*, 83(3): 1263-1295.

[39] Sutton, Paul C.; Elvidge, Christopher D.; and Ghosh, Tilottama (2007) "Estimation of gross domestic product at sub-national scales using nighttime satellite imagery." *International Journal of Ecological Economics & Statistics*, 8(S07): 5–21.

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, provides 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:

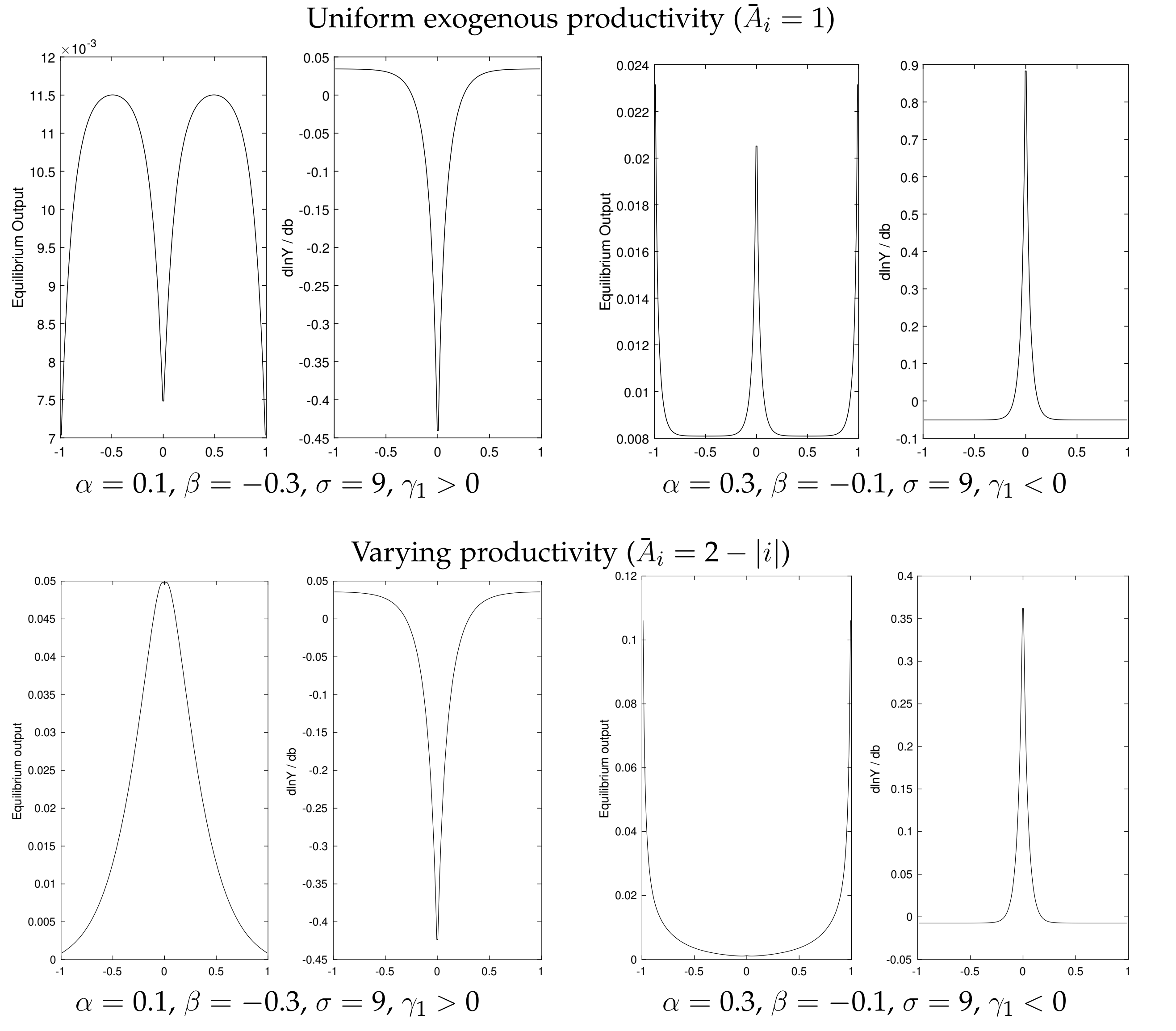
$$L_i^{(1-\alpha(\sigma-1)-\beta\sigma)} = (\bar{A}_i)^{(\sigma-1)}\left(W_{R(i)}\right)^{-\sigma}(P_i)^{1-2\sigma}(\bar{u}_i)^{\sigma}, \tag{9}$$

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

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

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.

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.

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 $\tau_{ij} = \exp\{\tau|i-j| + b\,(\text{sign}(i) \neq \text{sign}(j))\}$. 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.

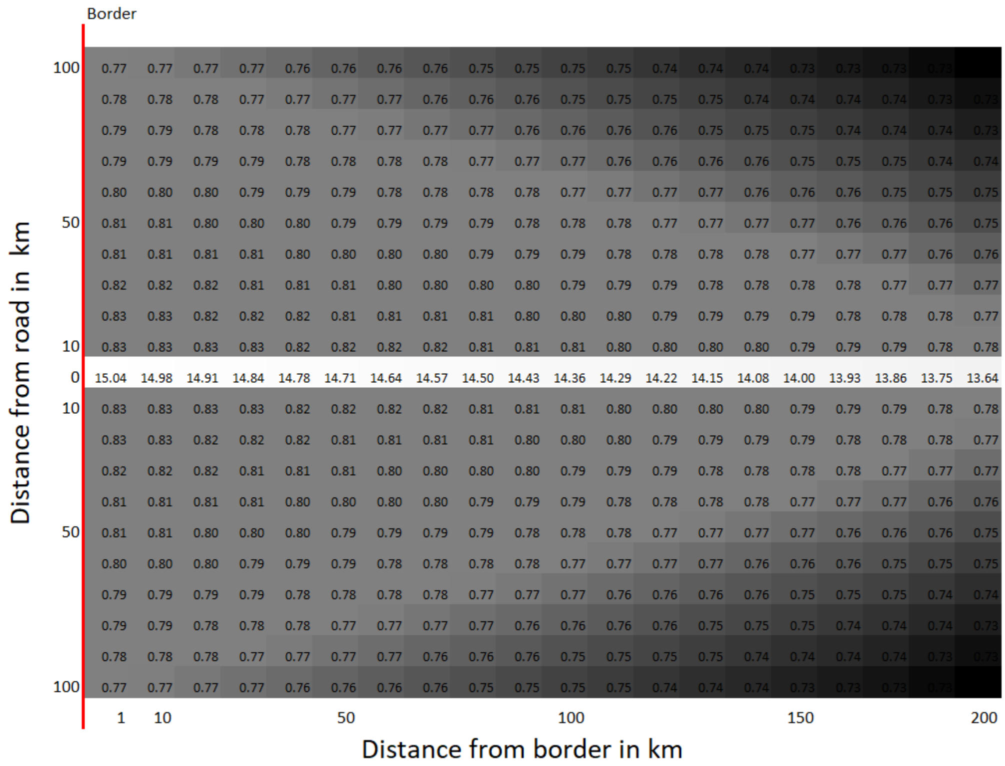
The location of *ports* is taken from the World Port Index published by the US National Geospatial-Intelligence Agency's Maritime Safety Office, and the location of *airports* is taken from Natural Earth.

Information on *altitude* is available through the Scripps Institution of Oceanography at the University of California Sand Diego, whose SRTM30 Plus dataset combines sea floor and land elevation data for the entire planet.

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 A14 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 value of the 25th percentile in our data (i.e. starting from the values presented in Figure 5, based on separate regressions for on-road and off-road grid cells, with road and country-year fixed effects, all control variables, and exports instrumented with tariffs. Darker colors symbolize lower light growth.

Table A1: Correlation between night lights and regional GDP

	(1)	(2)	(3)	(4)
	ln(GDP)	ln(GDP)	ln(GDP)	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		YES	YES	YES
Year FE			YES	
Country-year FE				YES

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	3.51	6.36	0	63	2,410,216
Distance from border	125.38	64.25	0.00	200	2,410,216
Total exports to neighbor country (in 100 mio US dollar)	345.83	815.92	0.00	3,460.35	2,410,216
Simple average applied tariff rate	6.36	7.85	0	81.03	2,154,764
Population count (people/grid cell)	4,843.03	24,388.84	0	3,473,122	1,984,099
Altitude	694.71	831.87	-419.89	6,499.86	2,410,216
Port dummy	0.22	0.41	0	1	2,410,216
Airport dummy	0.33	0.47	0	1	2,410,216
Distance from port (if port dummy = 1)	80.13	50.07	0	199.88	531,381
Distance from airport (if airport dummy = 1)	98.87	47.64	0	199.76	793,927
Dummy for light = 0	0.11	0.31	0	1	2,410,216

Table A3: Summary statistics: on-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	6.00	9.03	0	63	971,633
Distance from border	118.96	65.98	0.00	200	971,633
Total exports to neighbor country (in 100 mio US dollar)	354.39	806.57	0.00	3,460.35	971,633
Simple average applied tariff rate	5.80	7.72	0	81.03	879,422
Population count (people/grid cell)	9,208.55	36,837.67	0	3,473,122	802,034
Altitude	524.85	647.95	-414.97	5,796.10	971,633
Port dummy	0.28	0.45	0	1	971,633
Airport dummy	0.41	0.49	0	1	971,633
Distance from port (if port dummy = 1)	71.21	49.48	0	199.88	275,402
Distance from airport (if airport dummy = 1)	88.79	48.24	0	199.76	396,876
Dummy for light = 0	0.07	0.25	0	1	971,663

Table A4: Summary statistics: off-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	1.82	2.40	0	63	1,438,583
Distance from border	129.73	62.68	0.00	200	1,438,583
Total exports to neighbor country (in 100 mio US dollar)	340.06	822.12	0.00	3,460.35	1,438,583
Simple average applied tariff rate	6.75	7.92	0	81.03	1,275,342
Population count (people/grid cell)	1,881.01	7,480.52	0	326,600.30	1,182,065
Altitude	809.43	918.25	-419.89	6,499.86	1,438,583
Port dummy	0.18	0.38	0	1	1,438,583
Airport dummy	0.28	0.45	0	1	1,438,583
Distance from port (if port dummy = 1)	89.72	48.92	0	199.84	255,979
Distance from airport (if airport dummy = 1)	108.94	44.82	0	199.75	397,051
Dummy for light = 0	0.14	0.34	0	1	1,438,583

Table A5: Baseline estimates, excluding border-crossing grid cells

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Light intensity by grid cell and year (Y_{it})	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Panel A: On-road grid cells only					
Bilateral exports (in logs)	0.076***	0.588	0.016***	0.248**	0.030***
	(0.022)	(0.715)	(0.003)	(0.108)	(0.006)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.038***	-0.151***	-0.011***	-0.036***	-0.018***
	(0.013)	(0.057)	(0.002)	(0.010)	(0.003)
K-P F statistic		4.50		4.50	
S-W F statistic (main effect)		11.69		11.69	
S-W F statistic (interaction)		137.93		137.93	
# Clusters	9,192	8,322	9,192	8,322	9,192
# Observations	955,365	863,791	955,365	863,791	955,365
Panel B: Off-road grid cells only					
Bilateral exports (in logs)	0.028***	0.239	0.010***	0.118	0.048***
	(0.007)	(0.275)	(0.002)	(0.085)	(0.009)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.014***	-0.036***	-0.004***	-0.011***	-0.022***
	(0.004)	(0.014)	(0.001)	(0.004)	(0.005)
K-P F statistic		1.12		1.12	
S-W F statistic (main effect)		2.36		2.36	
S-W F statistic (interaction)		287.07		287.07	
# Clusters	8,815	8,043	8,815	8,043	8,810
# Observations	1,417,124	1,256,178	1,417,124	1,256,178	1,417,102
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	0.051***	0.318	0.013***	0.180**	0.043***
	(0.012)	(0.390)	(0.002)	(0.091)	(0.007)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.024***	-0.088***	-0.007***	-0.022***	-0.020***
	(0.007)	(0.028)	(0.001)	(0.007)	(0.004)
K-P F statistic		2.32		2.32	
S-W F statistic (main effect)		5.36		5.36	
S-W F statistic (interaction)		272.19		272.19	
# Clusters	9,791	8,933	9,791	8,933	9,791
# Observations	2,372,494	2,119,975	2,372,494	2,119,975	2,372,494
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

*** 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: Baseline estimates, without small countries

Dependent variable: Light intensity: $\log(Y_{it} + 1)$	(1) Baseline IV	(2) No small countries IV
Bilateral exports (in logs)	0.245**	0.211**
	(0.108)	(0.094)
Bilateral exports (in logs) $\times$ Distance from border (in 100km)	-0.035***	-0.035***
	(0.010)	(0.014)
K-P F statistic	4.50	6.01
S-W F statistic (main effect)	11.54	23.13
S-W F statistic (interaction)	138.69	101.77
# Clusters	8,361	3,394
# Observations	869,463	513,445
Grid cell FE	YES	YES
Country-year FE	YES	YES

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 A7: Baseline estimates, country-year level error clustering

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1)	(2)	(3)	(4)	(5)
	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Panel A: On-road grid cells only					
Bilateral exports (in logs)	0.077^{**}	0.572	0.016^{***}	0.246	0.029^{***}
	(0.031)	(1.218)	(0.005)	(0.178)	(0.008)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.038^{**}	-0.146	-0.010^{***}	-0.035^{***}	-0.017^{***}
	(0.017)	(0.101)	(0.003)	(0.013)	(0.004)
K-P F statistic		1.22		1.22	
S-W F statistic (main effect)		5.54		5.54	
S-W F statistic (interaction)		49.13		49.13	
# Clusters	597	580	597	580	597
# Observations	965,428	872,959	965,428	872,959	965,428
Panel B: Off-road grid cells only					
Bilateral exports (in logs)	0.028^{***}	0.240	0.010^{***}	0.117	0.048^{***}
	(0.009)	(0.373)	(0.003)	(0.128)	(0.014)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.014^{***}	-0.036^{*}	-0.004^{***}	-0.011^{*}	-0.023^{***}
	(0.004)	(0.021)	(0.001)	(0.007)	(0.006)
K-P F statistic		0.37		0.37	
S-W F statistic (main effect)		0.79		0.79	
S-W F statistic (interaction)		64.62		64.62	
# Clusters	602	586	602	586	600
# Observations	1,420,199	1,259,138	1,420,199	1,259,138	1,420,177
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	0.051^{***}	0.311	0.013^{***}	0.178	0.042^{***}
	(0.018)	(0.598)	(0.004)	(0.139)	(0.011)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.023^{**}	-0.086^{*}	-0.007^{***}	-0.022^{**}	-0.019^{***}
	(0.010)	(0.050)	(0.002)	(0.010)	(0.005)
K-P F statistic		0.75		0.75	
S-W F statistic (main effect)		2.22		2.22	
S-W F statistic (interaction)		80.83		80.83	
# Clusters	602	586	602	586	602
# Observations	2,385,632	2,132,103	2,385,632	2,132,103	2,385,632
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

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

Table A8: 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	-0.006^{**}	-0.031^{***}	-0.001	-0.002
	(0.003)	(0.010)	(0.001)	(0.001)
Average applied tariff rate × Distance from border (in 100km)	0.004^{***}	0.013^{**}	0.001^{***}	0.001^{*}
	(0.001)	(0.006)	(0.000)	(0.001)
# Clusters	10,653	1,405	10,653	1,405
# Observations	2,502,351	2,517,9791	2,502,351	2,517,979
Grid cell FE	YES	NO	YES	NO
Road FE	NO	YES	NO	YES
Country-year FE	YES	YES	YES	YES

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

Two-way clustered standard errors at grid cell and region-year level for (1) and (3) in parentheses.

Two-way clustered standard errors at road and country pair-year level for (2) and (4) in parentheses.

Table A9: Baseline estimates, exports instrumented with shift share instrument

Dependent variable: Light intensity by grid cell and year (Y_{it})	(1)	(2)	(3)	(4)	(5)
	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Panel A: On-road grid cells only					
Bilateral exports (in logs)	0.076***	0.046	0.016***	0.014	0.029***
	(0.022)	(0.170)	(0.003)	(0.026)	(0.006)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.038***	-0.067**	-0.010***	-0.021***	-0.017***
	(0.013)	(0.028)	(0.002)	(0.004)	(0.003)
K-P F statistic		53.83		53.83	
S-W F statistic (main effect)		356.55		356.55	
S-W F statistic (interaction)		1,442.68		1,442.68	
# Clusters	9,229	8,265	9,229	8,265	9,229
# Observations	961,696	880,094	961,696	880,094	961,696
Panel B: Off-road grid cells only					
Bilateral exports (in logs)	0.028***	-0.015	0.010***	0.003	0.048***
	(0.007)	(0.048)	(0.002)	(0.013)	(0.009)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.014***	-0.027***	-0.004***	-0.010***	-0.022***
	(0.004)	(0.009)	(0.001)	(0.002)	(0.005)
K-P F statistic		48.46		48.46	
S-W F statistic (main effect)		317.11		317.11	
S-W F statistic (interaction)		516.81		516.81	
# Clusters	8,815	7,868	8,815	7,868	8,810
# Observations	1,417,124	1,265,197	1,417,124	1,265,197	1,417,102
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	0.051***	-0.001	0.013***	0.009	0.041***
	(0.012)	(0.086)	(0.002)	(0.017)	(0.007)
Bilateral exports (in logs) × Distance from border (in 100km)	-0.023***	-0.043***	-0.007***	-0.014***	-0.019***
	(0.007)	(0.017)	(0.001)	(0.003)	(0.004)
K-P F statistic		54.01		54.01	
S-W F statistic (main effect)		412.13		412.13	
S-W F statistic (interaction)		734.36		734.36	
# Clusters	9,814	8,748	9,814	8,748	9,814
# Observations	2,378,825	2,145,296	2,378,825	2,145,296	2,378,825
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

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

Table A10: Baseline effects for light intensity per capita and population

	(1)	(2)	(3)	(4)
Dependent variable:	Lights per capita (logs)		Population (logs)	
	OLS	IV	OLS	IV
Panel A: On-road grid cells				
Bilateral exports (in logs)	0.006**	0.045*	0.000	0.016
	(0.002)	(0.026)	(0.004)	(0.051)
Bilateral exports × Distance from border (in 100km)	-0.001	-0.002	-0.005***	-0.015***
	(0.001)	(0.001)	(0.002)	(0.006)
K-P F statistic		1.84		1.85
S-W F statistic (main effect)		5.12		5.15
S-W F statistic (interaction)		543.30		524.81
# Clusters	7,676	7,312	7,676	7,312
# Observations	789,372	736,618	792,989	740,199
Panel B: Off-road grid cells				
Bilateral exports (in logs)	0.003***	0.034	0.006	0.032
	(0.001)	(0.021)	(0.003)	(0.030)
Bilateral exports × Distance from border (in 100km)	-0.003***	-0.001	-0.000	-0.021***
	(0.001)	(0.002)	(0.001)	(0.006)
K-P F statistic		3.36		3.23
S-W F statistic (main effect)		18,99		17.19
S-W F statistic (interaction)		301.09		294.13
# Clusters	7,342	6,992	7,342	6,992
# Observations	1,126,306	1,030,790	1,160,720	1,064,722
Panel C: On-road + off-road grid cells				
Bilateral exports (in logs)	0.004***	0.033*	0.004	0.034
	(0.001)	(0.019)	(0.003)	(0.030)
Bilateral exports × Distance from border (in 100km)	-0.002***	-0.001	-0.001	-0.019***
	(0.001)	(0.001)	(0.001)	(0.005)
K-P F statistic		3.38		3.28
S-W F statistic (main effect)		16.16		15.12
S-W F statistic (interaction)		434.21		423.40
# Clusters	8,156	7,794	8,156	7,794
# Observations	1,915,682	1,767,413	1,953,713	1,804,926
Grid cell FE	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES

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

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

Table A11: Imports

Dependent variable: Light intensity (Y_{it})	(1) Levels: Y_{it} OLS	(2) IV	(3) Logs: $\ln(Y_{it}+1)$ OLS	(4) IV	(5) Levels: Y_{it} Poisson
Panel A: On-road grid cells					
Bilateral imports (in logs)	0.064^{***}	-0.524	0.015^{***}	-0.314	0.035^{***}
	(0.017)	(0.538)	(0.003)	(0.197)	(0.005)
Bilateral imports $\times$ Distance from border (in 100km)	-0.040^{***}	-0.042	-0.010^{***}	-0.025^{***}	-0.021^{***}
	(0.010)	(0.043)	(0.002)	(0.009)	(0.003)
K-P F statistic		1.71		1.71	
S-W F statistic (main effect)		4.23		4.23	
S-W F statistic (interaction)		550.20		550.20	
# Clusters	9,207	8,480	9,207	8,480	9,207
# Observations	970,969	909,139	970,969	909,139	970,969
Panel B: Off-road grid cells					
Bilateral imports (in logs)	0.014^{***}	-0.150	0.005^{***}	-0.092^{**}	0.027^{***}
	(0.005)	(0.092)	(0.001)	(0.046)	(0.007)
Bilateral imports $\times$ Distance from border (in 100km)	-0.010^{***}	-0.027^{*}	-0.004^{***}	-0.011^{***}	-0.019^{***}
	(0.003)	(0.014)	(0.001)	(0.004)	(0.004)
K-P F statistic		3.06		3.06	
S-W F statistic (main effect)		34.10		34.10	
S-W F statistic (interaction)		324.53		324.53	
# Clusters	8,815	8,129	8,815	8,129	8,810
# Observations	1,429,568	1,318,335	1,429,568	1,318,335	1,429,546
Panel C: On-road + off-road grid cells					
Bilateral imports (in logs)	0.030^{***}	-0.191	0.008^{***}	-0.126^{*}	0.029^{***}
	(0.010)	(0.156)	(0.002)	(0.067)	(0.006)
Bilateral imports $\times$ Distance from border (in 100km)	-0.023^{***}	-0.035	-0.006^{***}	-0.018^{***}	-0.021^{***}
	(0.006)	(0.028)	(0.001)	(0.006)	(0.003)
K-P F statistic F statistic		2.92		2.92	
S-W F statistic (main effect)		21.68		21.68	
S-W F statistic (interaction)		434.05			434.05
# Clusters	9,804	9,063	9,804	9,063	9,804
# Observations	2,400,542	2,227,474	2,400,542	2,227,474	2,400,542
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

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

Table A12: Developing and advanced economies

Dependent variable: Light intensity (Y_{it})	(1)	(2)	(3)	(4)	(5)
	Levels: Y_{it}		Logs: $\ln(Y_{it}+1)$		Levels: Y_{it}
	OLS	IV	OLS	IV	Poisson
Panel A: On-road grid cells					
Bilateral exports (in logs)	0.081***	0.778**	0.016***	0.118	0.038***
	(0.020)	(0.363)	(0.003)	(0.072)	(0.007)
Bilateral exports × Distance from border (in 100km)	-0.040***	-0.114**	-0.009***	-0.018*	-0.021***
	(0.011)	(0.044)	(0.002)	(0.009)	(0.004)
Advanced economy (dummy) × Bilateral exports	-0.046	-1.468	-0.011	0.865	-0.035**
	(0.113)	(4.950)	(0.016)	(0.564)	(0.015)
Advanced economy × Distance from border × Bilateral exports	0.011	-0.366	-0.009	-0.036	0.008
	(0.067)	(0.273)	(0.010)	(0.047)	(0.008)
K-P F statistic		1.83		1.83	
S-W F statistic (triple interaction)		163.52		163.52	
# Clusters	9,229	8,361	9,229	8,361	9,229
# Observations	961,696	869,463	961,696	869,463	961,696
Panel B: Off-road grid cells					
Bilateral exports (in logs)	0.028***	0.204	0.009***	0.077	0.050***
	(0.006)	(0.228)	(0.002)	(0.071)	(0.009)
Bilateral exports × Distance from border (in 100km)	-0.012***	-0.018	-0.004***	-0.004	-0.022***
	(0.003)	(0.012)	(0.001)	(0.004)	(0.005)
Advanced economy (dummy) × Bilateral exports	-0.009	0.331	0.003	0.298	-0.032
	(0.060)	(1.210)	(0.014)	(0.238)	(0.049)
Advanced economy × Distance from border × Bilateral exports	-0.031	-0.144**	-0.009	-0.057***	-0.012
	(0.030)	(0.063)	(0.006)	(0.018)	(0.023)
K-P F statistic		0.40		0.40	
S-W F statistic (triple interaction)		360.91		360.91	
# Clusters	8,815	8,043	8,815	8,043	8,810
# Observations	1,417,124	1,256,178	1,417,124	1,256,178	1,417,102
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	0.051***	0.346	0.013***	0.113	0.050***
	(0.011)	(0.258)	(0.002)	(0.072)	(0.008)
Bilateral exports × Distance from border (in 100km)	-0.021***	-0.043*	-0.006***	-0.008	-0.021***
	(0.006)	(0.022)	(0.001)	(0.006)	(0.004)
Advanced economy (dummy) × Bilateral exports	-0.017	-0.123	-0.004	0.502	-0.048**
	(0.087)	(2.505)	(0.014)	(0.340)	(0.020)
Advanced economy × Distance from border × Bilateral exports	-0.032	-0.330***	-0.011	-0.080***	0.006
	(0.050)	(0.118)	(0.009)	(0.027)	(0.012)
K-P F statistic		0.90		0.90	
S-W F statistic (triple interaction)		364.51		364.51	
# Clusters	9,814	8,957	9,814	8,957	9,814
# Observations	2,378,825	2,125,647	2,378,825	2,125,647	2,378,825
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

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

Table A13: Effects by continent

Dependent variable: Light intensity: $\log(Y_{it}+1)$	(1) Africa IV	(2) Asia IV	(3) Europe IV	(4) Latin America IV	(5) North America IV
Panel A: On-road grid cells					
Bilateral exports (in logs)	-0.012	0.176	-0.018	-0.107	0.717**
	(0.020)	(0.130)	(0.075)	(0.238)	(0.292)
Bilateral exports × Distance from border (in 100km)	-0.011**	-0.014	-0.103***	0.000	-0.199**
	(0.005)	(0.021)	(0.015)	(0.012)	(0.096)
K-P F statistic	3.46	3.54	20.40	0.39	9.38
S-W F statistic (main effect)	37.57	8.90	58.01	1.92	28.49
S-W F statistic (interaction)	192.43	49.55	868.81	173.39	23.83
# Clusters	2,083	2,031	2,824	1,339	150
# Observations	147,276	171,762	331,287	99,784	119,345
Panel B: Off-road grid cells					
Bilateral exports (in logs)	-0.003	-0.546	0.024	-0.010	0.417**
	(0.004)	(1.483)	(0.106)	(0.028)	(0.175)
Bilateral exports × Distance from border (in 100km)	-0.003**	0.020	-0.102***	0.003	-0.171***
	(0.001)	(0.042)	(0.015)	(0.004)	(0.047)
K-P F statistic	4.99	0.07	6.40	7.97	11.30
S-W F statistic (main effect)	66.23	0.18	25.70	27.65	32.96
S-W F statistic (interaction)	105.77	2.40	532.92	168.91	27.03
# Clusters	2,092	2,104	2,390	1,371	150
# Observations	299,210	365,181	206,058	206,424	179,305
Panel C: On-road + off-road grid cells					
Bilateral exports (in logs)	-0.008	0.860	0.001	-0.007	0.589**
	(0.010)	(1.978)	(0.084)	(0.051)	(0.231)
Bilateral exports × Distance from border (in 100km)	-0.005*	-0.039	-0.111***	0.002	-0.220***
	(0.003)	(0.108)	(0.016)	(0.006)	(0.076)
K-P F statistic	5.43	0.09	13.71	4.27	11.28
S-W F statistic (main effect)	77.13	0.19	48.89	17.82	32.81
S-W F statistic (interaction)	140.18	0.91	861.16	176.32	27.73
# Clusters	2,275	2,269	2,897	1,439	155
# Observations	446,486	536,943	537,355	306,209	298,650
Grid cell FE	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES

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

Table A14: Summary statistics: crops

Crop	# observations	Percent
Barley	38,503	8.28
Cotton	22,643	4.87
Groundnut	4,354	0.94
Maize	127,040	27.32
Rice	64,825	13.94
Sorghum	12,572	2.70
Soybean	19,159	4.12
Sugarcane	3,733	0.80
Sunflower	13,374	2.88
Wheat	158,723	34.14
Total	464,926	100.00