Let There Be 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 relative to interior regions? Theory tends to suggest that trade helps, but it can also predict the reverse. The question is policy relevant as regions near land borders are generally poorer, and sometimes more prone to civil conflict, than interior regions. We therefore estimate how changes in bilateral trade volumes affect economic activity along roads running inland from international borders, using satellite night-light measurements for 2,186 border-crossing roads in 138 countries. We observe a significant 'border shadow': on average, lights are 37 percent dimmer at the border than 200 kilometers 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. At the mean, a doubling of exports to a particular neighbor country reduces the gradient of light from the border by some 23 percent. This qualitative finding applies to developed and developing countries, and to rural and urban border regions. Proximity to cities on either side of the border amplifies the effects of trade. We provide evidence that local export-oriented production is a significant mechanism behind the observed effects.

JEL Classification: F14, F15, R11, R12

Keywords: Trade liberalization, border regions, economic geography, night lights data

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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 literally are darker: night lights captured by satellites are on average 37 percent less intense at land borders than 200 road kilometers inland. 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.

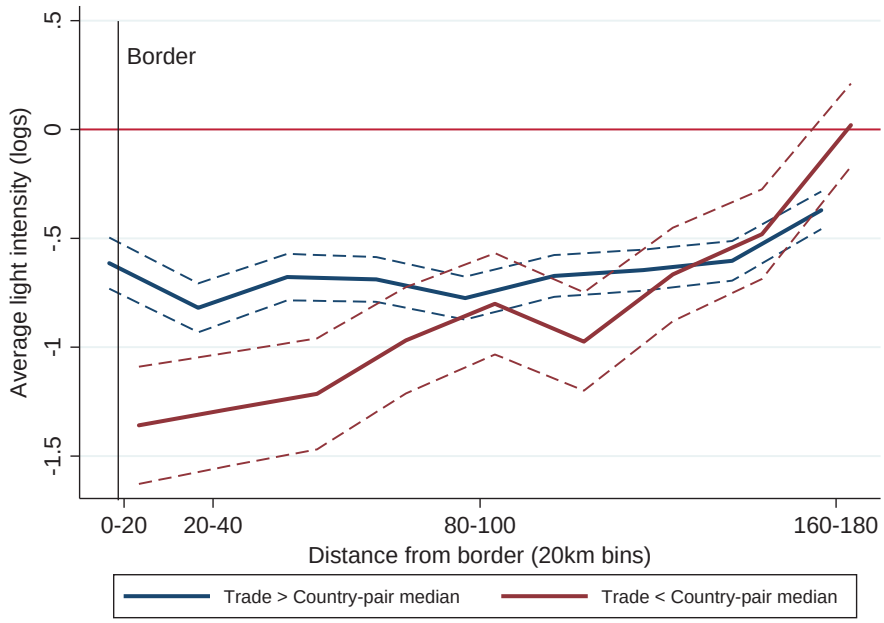
The effect of trade on the economic development of border regions is of academic interest because theory can accommodate both scenarios, whereby trade either favors or impedes the economic catch-up of border regions. Trade-induced catch-up emerges most naturally from quantitative geography models. However, sectoral specialization or agglomeration effects, if strong enough, can lead to interior regions gaining disproportionately from trade liberalization. Ours is the first study to investigate this question empirically across multiple countries, and our results strongly suggest that trade liberalization disproportionately boosts border-region economies.

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. 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. 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 potentially severe measurement problem can be overcome by drawing on satellite night lights data. We follow this approach and test how cross-border trade affects light gradients with respect to distance from the border. An additional difficulty for empirical analysis is that causation between changes in cross-border trade volumes and changes in border-region economic conditions could run both ways. We therefore instrument bilateral exports with import tariffs on the opposite side of the border, allowing us to identify plausibly causal effects running from trade to border-region economic development.

Our main results can be summarized as follows. Measuring light intensity along all major cross-border road corridors over the 1995-2013 period, we detect a distinct border shadow, whereby average light intensity progressively decreases as one gets closer to the border. The effect is robust to the inclusion of geographical controls (altitude, proximity of ports and airports) as well as to the inclusion of region-year fixed effects to control for confounding political-economy influences. Most importantly, we show that trade liberalization, measured

Figure 1: Within-road light gradients as a function of trade intensity



Note: The graph shows point estimates of a within-road regression according to equation (1) of Section 4.2.1, where distance from the border is modeled as a set of dummy variables for bins of 20km width. The sample of world-wide night-light observations is split into "high trade" (blue line) and "low trade" (red line) years. A road-year observation is counted as high-trade (low-trade) if overall exports from country i to country j in this year were above (below) the sample average of exports between the two countries. The graph plots estimates for all distance bins up to 200 kilometers from the border, with the most distant bin taken as the reference group. Dashed lines are 95% confidence intervals.

by the volume of exports between the two countries separated by a border, reduces the intensity of the border shadow. This effect too is robust to the inclusion of an array of controls, and it seems to be driven to a significant extent by local export-oriented production.

Figure 1 illustrates this striking regularity. The graph is constructed in such a way that the observed difference in border shadows is identified through time variation and therefore cannot be attributed to natural features that facilitate both cross-border trade and border-region development. We observe a border shadow that is visibly stronger in low-trade years than in high-trade years, and this up to a distance from the border of some 150 kilometers. In what follows, we describe in detail how this qualitative finding also emerges when estimated more rigorously, how it covaries with other observables, and what mechanisms likely underpin it.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, Section 3 describes the data, Section 4 discusses estimation issues, Section 5 presents baseline results, Section 6 presents extensions, and Section 7 concludes.

2 Literature background

2.1 Theory

Within-country spatial effects of external trade liberalization have been modeled in a number of recent theoretical contributions, yielding tractable quantitative spatial models with rich underlying geographies (Allen and Arkolakis, 2014; Atkin and Donaldson, 2015; Cosar and

Fajgelbaum, 2016; Fajgelbaum and Redding, 2018; Redding, 2016; Rossi-Hansberg, 2005).[1] 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.

Improved market access acts as a potential (but not necessary!) boon for regional economies in all these models. Specifically, all spatial general-equilibrium models known to us that feature heterogeneous regions and labor mobility within countries can generate disproportionate economic growth in border regions as a consequence of external trade liberalization – where we associate 'border regions' with relatively low transport costs to the international border. The nature of the response depends on the specifics of the model. In counterfactual simulations of falling crossborder trade costs, border regions experience a combination of higher employment, higher real wages, higher consumer surplus and/or higher land rents.

Importantly, alternative configurations are also possible. 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. 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. Consideration of intra-national transport costs makes the effective gain in market access associated with a certain drop in the cross-border trade cost unequal along the border, depending on the size of the adjacent market in the neighboring country. In our estimations, we therefore take account of urbanization patterns on either side of the border. General-equilibrium effects furthermore imply that trade liberalization triggers a reallocation of activity among different segments of the border region, such that the gains in economic activity in some border areas might come at the expense of economic activity in some other border areas.

Redding (2016, Section 5.5) simulates a hypothetical two-country world with a road running perpendicular to the border. This is the theoretical setup that comes closest to our empirical configuration. 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. Our aims in this paper are to explore the generality of this qualitative prediction and to quantify the average effect at the border and its decay in space using actual rather than simulated data. 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. We shall explore the empirical relevance of

[1] 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.

this prediction as well.

2.2 Empirics

The dominant theoretical prediction whereby trade liberalization is favorable to the development of border regions is borne out in a majority of existing cross-country empirical analyses. Following the seminal paper by Ades and Glaeser (1995), a considerable number of studies have found trade openness to be associated with the spatial dispersion of activities within countries.[2] This is consistent with economic catch-up by border regions.

Within-country studies show more mixed results, partly because many of them focus 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).[3]

More recent papers have used the closing-off of central and eastern European markets after World War II and their reopening after the fall of the Berlin Wall as a natural experiment. 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 is found to have had a significantly positive effect on the population growth of border regions in Germany (Redding and Sturm, 2008) and on employment and wages in Austrian border regions (Brülhart, Carrère and Trionfetti, 2012). Both papers document border shadows, whereby, in the Cold War years, population density, employment density and wages progressively fell as one got closer to the Iron Curtain, which represented an almost insuperable barrier to trade. After the demise of the communist bloc, growth was stronger in German and Austrian cities 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.[4] 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 variables 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 quantify effects at the border as well as gradients as one moves away from border crossing points.

Among the extensions to our baseline estimation, we explore the impact of export growth on the incidence of violent conflict in border regions. While there exists a political-science literature on the impact of trade on the probability of conflict, sometimes labeled the "commercial peace" hypothesis, this literature mainly focuses on interstate disputes (see e.g. Schultz, 2015).[5]

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

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

[4]Hirte, Lessmann and Seidel (2018) 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.

[5]Cantens and Raballand (2017) offer a case-study based analysis of the role of cross-border trade for conflict-

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 on-road grid cells
Advanced economies	3.96	70.07	17.71	1,159	149,944
Developing economies	4.31	20.40	4.74	1,071	499,165

Note: Countries grouped according to 2015 World Bank classification.

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.[6] On the whole, night lights have been found to represent a good proxy for economic activity and human development at the local level (Bruederle and Hodler, 2018). 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.[7] While this scale represents the luminosity of light proportionally, pixels with the value of 63 may be top censored. This on average concerns some 0.1 percent 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 45 percent in South Asia to 92 percent in Sub-Saharan Africa.

Our analysis focuses on locations within 200 kilometers of international land borders.[8] Distance from the border is measured along *road corridors*.[9] We consider all border-crossing major roads according to the 1990 version of the ESRI Roads and Highways dataset (see Figure 2).[10] Our analysis is thus based on 2,230 border crossings. As shown in Table 1, we observe 70 land border crossings in the average advanced economy but only 20 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 48% 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

prone border regions in Africa. They document vividly how trade-related activities can help conflict resolution for example by offering economic opportunities to former fighters or by redeploying vehicles from military to civil transport uses.

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

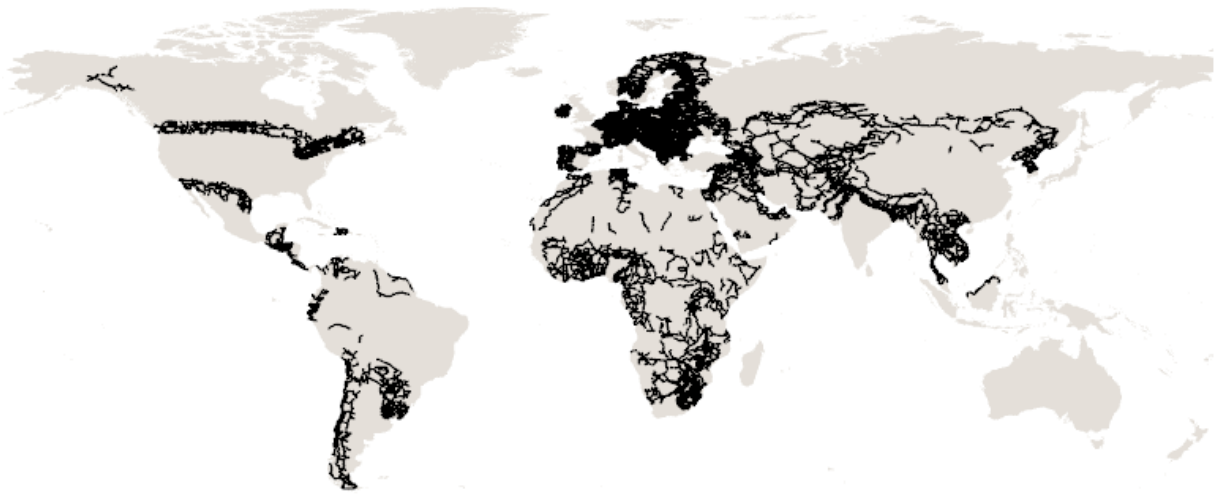
[7]We in addition drop cells featuring lights emitted by gas flares – which do not proxy well for economic activity – using readily available information on their location (see Henderson, Storeygard and Weil, 2012).

[8]Our qualitative results do not hinge on this cutoff (see Appendix Table A6).

[9]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.

[10]The identification of "major" roads is based on information provided by national authorities. Since all our estimations are based on 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 ESRI Roads and Highways dataset.

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 either a "highway" or a "major road" in the ESRI dataset. The figure illustrates how lights cluster along major roads. 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.

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 ten kilometers on either side of the border-crossing roads. We also consider additional outer buffers with a width of 200 kilometers. 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 162,000 grid cells for each of the years 1995, 2000, 2005 and 2010 (the years for which gridded population data are also available).[11] For each on-road 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.[12]

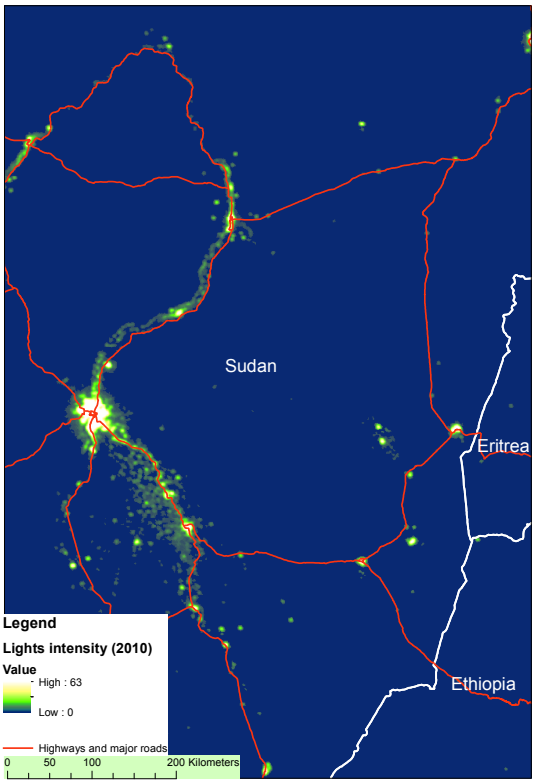
Detailed information on all our data sources and definitions is provided in Appendix A.

[11]The DMSP satellites were discontinued in 2013 and replaced by a new system of satellites called VIIRS. As there is no consensus on how to convert values from different satellites to a unified scale (see, e.g., Chen and Nordhaus, 2015), we limit our baseline panel to five-year intervals from 1995 to 2010. In Appendix B we also provide results for estimations including the lights data of 2013, showing that none of our findings are sensitive to the inclusion or exclusion of that additional year of data.

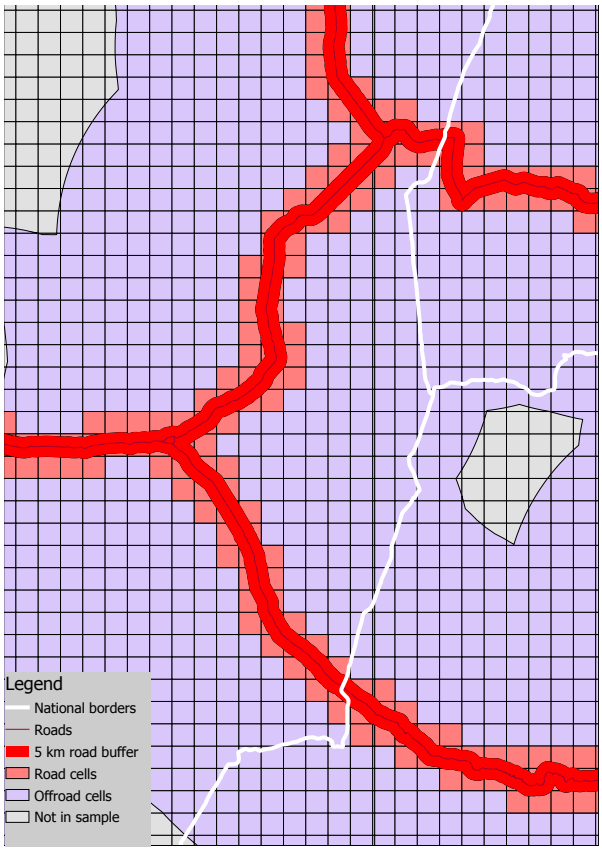
[12]Summary statistics for all variables are given in Appendix Tables A1 (all observations), A2 (on-road observations only) and A3 (off-road observations only).

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 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.

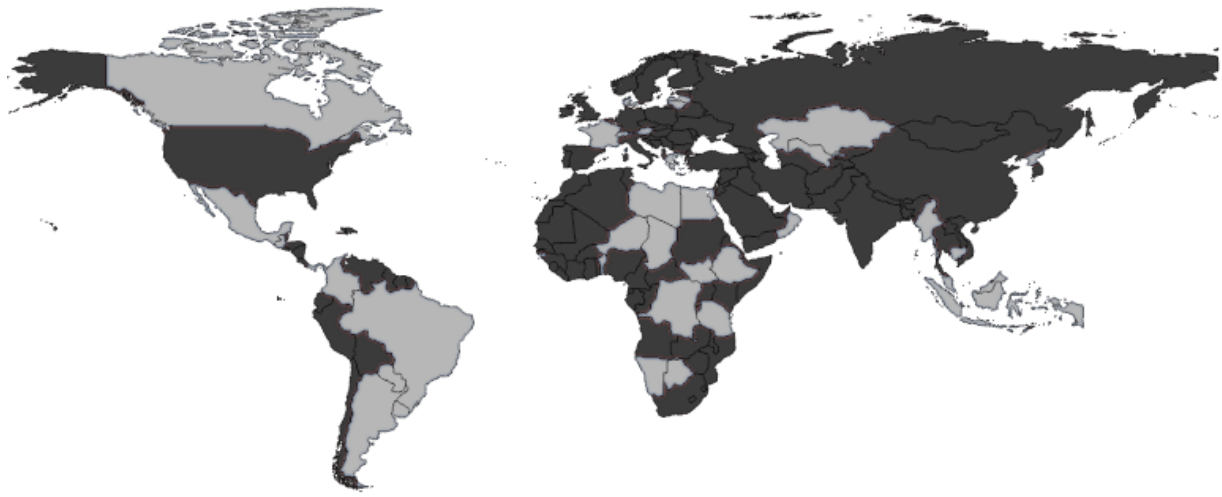
3.2 The border shadow

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 of light intensity compared to non-border regions. To do so, we compute average light intensities within countries separately for grid cells located within 200 kilometers of land borders (the "border region") and for grid cells located beyond 200 kilometers of the nearest land border (the "interior region", which includes coastal locations provided that they are more than 200 kilometers from a border).[13] The results are shown in Figure 4, where all countries featuring border regions that are relatively darker than the respective interior regions are colored black. 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 (105 of the 138 countries shown in Figure 4). Weighted by population, these account for 80% of the sample, and weighted by GDP, they account for 83% of the sample.

[13]For countries that are too small to host an interior region according to this definition, we decrease the cutoff distance in increments of 25 kilometers until the interior region becomes non-empty. Dropping those small countries does not significantly alter our results (see column (3) of Appendix Table A13).

Figure 4: Dark land border regions dominate



Note: Sample countries are displayed according to the average light intensities in border regions in relation to the respective country average before conditioning on any covariates. In dark gray countries, border regions, defined as within up to 200 kilometers, are on average darker than interior and coastal regions, and vice-versa for light gray countries.

Table 2: Average light intensity by distance from border (scale: 0-63)

	Mean	Std. dev.	t stat.	No. obs.
$0-100$ km distance from border	3.12	8.05		345,326
$100-200$ km distance from border	4.17	12.39		303,783
Difference	-1.05		-54.32	

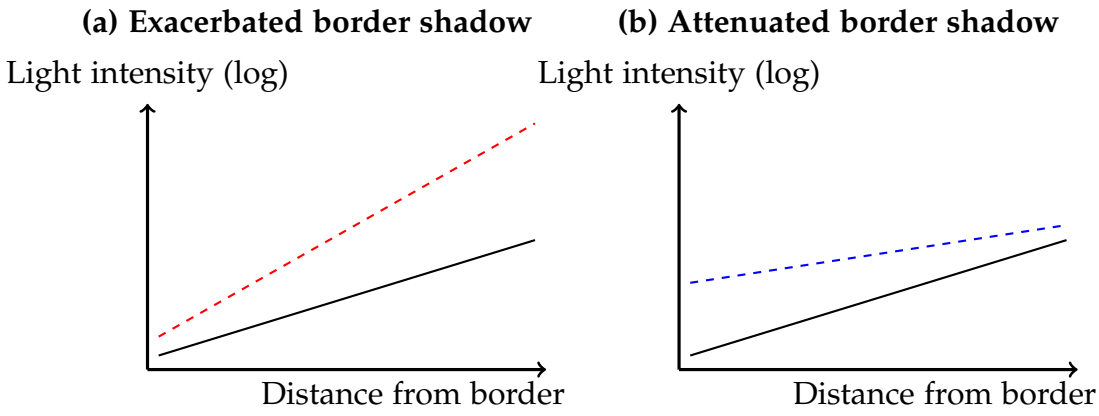
Our main approach in this paper is to consider light gradients within 200 kilometers of land borders. Within this range, the raw average light intensity score in the outer distance band (100-200 kilometers from land borders) equals 4.17, but that in the inner distance band (0-100 kilometers) is only 3.12. As shown in Table 2, the difference is statistically significant.[14] The averages shown in Table 2 understate the steepness of the gradient, because they aggregate lights by broad distance band. Our average observed light intensity for on-road cells at 100 kilometers from the border is 3.41 and at 200 kilometers it is 4.75, while the average light intensity at the border crossing is 2.97.[15] Hence, grid cells at the border are on average 13 percent darker than grid cells 100 kilometers inland and fully 37 percent darker than grid cells 200 kilometers inland.

The location of borders, of course, is not random and often coincides with inhospitable terrain. Part of the observed gradient is therefore undoubtedly explained by the endogeneity of border locations and not reflective of any man-made barriers to trade. However, as we document below, a strongly positive light gradient in distance from the border persists in the data once we control for topography. This implies that, while borders typically cross "naturally dark" regions, they cast an additional shadow over these regions.

[14] As an illustration, Appendix Figure A1 maps average lights within these two distance bands for the countries of Sub-Saharan Africa.

[15] See Appendix Table A1.

Figure 5: Trade and the border shadow – two scenarios



Note: The solid lines illustrate the border shadow before trade liberalization. The dashed lines illustrate border shadows after trade liberalization.

4 Estimation

4.1 Two scenarios

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, which we illustrate in Figure 5. If the productivity advantages of interior regions were to outweigh their disadvantage from greater distance from the border, then the interior of the country could benefit more from the liberalization than the border region, thus steepening the lights gradient (panel a). Conversely, trade liberalization might flatten the lights gradient and therefore brighten up the border shadow (panel b). As discussed in Section 2.1, theory can accommodate both configurations.

Note that our two stylized scenarios illustrated in Figure 5 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.[16] 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.

In Figure 5, we trace a linear relationship between distance from the border and the log of light intensity. Other functional forms are conceivable, such as for example a non-monotonic relationship with high light intensity at the border followed by decreasing light intensity in proximity to the border and growing light intensity as one moves further towards the interior. We however find the loglinear approximation to perform well. Our estimated light gradients are not significantly different when we drop grid cells located directly at the border crossing, and estimates of polynomial terms of distance are small and statistically insignificant.[17] When we vary the cut-off distances from the border (our baseline being 200 kilometers), we find the lights gradient to be positive throughout and if anything somewhat steeper close to the

[16]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).

[17]See Appendix Tables A4 and A5 respectively.

border.[18] For the remainder of our analysis we therefore maintain the assumption of a linear relationship between distance from the border and the log of light intensity.

4.2 Baseline estimation

4.2.1 On-road locations only

Our baseline empirical strategy consists of estimating night-light distance gradients along major roads across all of the world's land borders. In order to capture the causal effect of borders, we control for confounding influences arising from other exogenous sources of spatial heterogeneity such as altitude or proximity to ports and airports. Moreover, we systematically include fixed effects in order to remove country or even region-specific heterogeneity, as Pinkovskiy (2017) shows that night lights exhibit significant nation-specific variation.

Specifically, let $y_{irscc't} = y_{it}$ be the log light intensity of grid cell i located on road r in sub-national region s leading from country c to country c' in year t.[19] Roads r are defined as belonging to one country only, such that every cross-border road corridor consists of two "roads". The subscripts r, s, c and c' are implied by i, as every cell is uniquely assigned to a country, region and nearest road. We denote by d_i^{border} cell i's distance from the nearest border crossing along road r. $T_{cc't}$ stands for the log value of trade of country c with neighboring country c' across that border, where trade is measured alternatively as exports from c to c' (our baseline) or as imports by c from c'.

When limited to on-road locations (red grid cells in Figure 3b), our empirical model can be written as follows:

$$y_{it} = \beta_0 + \beta_1 d_i^{border} + \beta_2 T_{cc't} + \beta_3 (d_i^{border} \times T_{cc't}) + \theta \mathbf{x}_i + \gamma_r + \gamma_{st} + \gamma_{c't} + u_{it} \tag{1}$$

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. We also include a dummy that takes the value of 1 if at the relevant border crossing the same ethnicity dominates on both sides of the border, a configuration that has been shown to affect cross-border economic relations (Muller and Pecher, 2018).

In addition to controlling for grid-cell-level geographical characteristics through $\mathbf{x}_i$, we include three sets of fixed effects with the aim of further allaying potential concerns over identification.

First, we add road fixed effects, γ_r. These fixed effects soak up any unobserved time-invariant specificities of particular roads affecting their average luminosity, such as the quality and capacity of the road.

Second, we include region-year fixed effects, γ_{st}, to control for unobserved political or other regional events that could change the gradient of economic activity along a certain road over time as well as being correlated with trade and trade policy.[20] For instance, well-connected local politicians in border areas might obtain privileged access to public funding (for roads, electrification etc.) while at the same time using their influence to push for trade-facilitation reforms benefiting primarily their (border) constituencies (Hodler and Raschky, 2014). Other examples of region-time-specific confounding factors are regional outbreaks of

[18] See Appendix Table A6.

[19] In order not to lose grid cells with zero measured lights through the log transformation, we add 0.01 to recorded lights. Alternatively setting this value to 0.1 or to 1 has no discernible impact on our results.

[20] Regions are defined at the highest sub-national administrative level, e.g. at the state level in the United States (hence the notation s).

violent conflict or the localized occurrence of extreme weather events. Region-year fixed effects add up to year fixed effects and therefore control for common time-varying determinants of measured light intensities, notably including differences in satellite capabilities over time. By adding up to country-year effects, they moreover control for country-level institutional and economic specificities.

Third, we allow for time-varying cross-border spillovers other than trade (e.g. through migration or investment surges) by controlling for neighbor-country-year effects $\gamma_{c't}$. The simultaneous inclusion of $\gamma_{c't}$ and γ_{st} implies that the identification of β_2 and β_3 relies on within region-year variation and is thus driven by regions from which at least two different neighbor countries can be reached within 200 kilometers. This is the case for 44.9% of the regions in our sample.

The joint inclusion of the three sets of fixed effects is very demanding for our estimations, as it strongly constrains the identifying variation left in our data. We therefore also explore the behavior of our estimates when including fewer than the three sets of fixed effects.

4.2.2 Including off-road locations

In order to explore the effect of trade liberalization on border-region grid cells located beyond 10 kilometers of a major border-crossing road, we expand equation (1) to incorporate also off-road locations (blue grid cells in Figure 3b):

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 d_i^{border} + \beta_2 T_{cc't} + \beta_3 (d_i^{border} \times T_{cc't}) \\ + \beta_4 \mathit{Off}_i + \mathit{Off}_i \left(\beta_5 d_i^{border} + \beta_6 d_i^{road} + \beta_7 T_{cc't} + \beta_8 d_i^{border} \times T_{cc't} + \beta_9 d_i^{road} \times T_{cc't} + \gamma_r \right) \\ + \theta \mathbf{x}_i + \gamma_r + \gamma_{st} + \gamma_{c't} + v_{it}, \end{aligned} \quad (2)$$

where Off_i is a dummy variable that takes the value of 1 if cell i is not within 10 kilometers of a major border-crossing road; and d_i^{road} is the geodesic distance of cell i to the nearest grid cell on a border-crossing road r (hence, $d_i^{road} = 0 \Leftrightarrow \mathit{Off}_i = 0$). All off-road grid cells are uniquely attributed to their nearest border-crossing road r.[21]

Our empirical model implies that we identify the effects of interest at the within-road (and thus within-country) level: the gradient of night lights along a certain road is compared across years. Our coefficients of main interest are β_1, β_2 and β_3. A significantly positive estimate of β_1 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 $T_{cc't} = 0$. β_2 captures the effect on night lights of increased cross-border trade at the border crossing (where $d_i^{border} = 0$), and the interaction term (β_3) allows us to gauge how increased trade affects the distance gradient. When β_3 has the same sign as β_1, the data support a trade-related exacerbation of the border shadow, otherwise they support an attenuation of the border shadow. 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, as in panel b of Figure 5. Finally, in specifications that include off-road grid cells, coefficients β_5 to β_9 allow for complementary evidence on the effect of trade on light gradients based on readings for those locations.

[21] We allow for different road-specific fixed effects for road and off-road cells, for the sake of comparability of coefficients across estimations with and without off-road cells. This means that the coefficient β_4 is absorbed by the fixed effects $\mathit{Off}_i \times \gamma_r$. Interacting all controls with Off_i (or, equivalently, estimating the model separately for on-road and off-road cells) does not qualitatively alter our results.

4.3 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 border-region economic activity can in turn affect the volume of cross-border trade. We therefore estimate equations (1) and (2) 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.[22]

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 tariffs of country c' affect economic activity in country c only through changes in the volume of exports from country c to c' – an assumption we consider similarly plausible.

Throughout the analysis, we cluster standard errors two ways, by road r and by country-pair-year $cc't$. Roads represent the main dimension of the fixed effects structure in our regression model (2), and country-pair-year is the dimension of variation of our trade variable.

Another potential challenge for identification would be systematically different pre-sample light intensities across regions with different within-sample export growth rates. If trade expansion were to favor geographical dispersion in general, and if originally darker border regions were on average to experience greater subsequent export growth, our estimated main effect of trade (β_3) might capture trade-induced regional dispersion rather than a specifically border-related effect. This turns out to be an unlikely configuration, as regions with export growth above and below the sample median have virtually identical pre-sample light intensities.[23]

Our approach to inference is conservative. The two-way clustered standard errors we report are larger than standard errors clustered one-way by road in a large majority of cases, and always with respect to our interaction coefficients of main interest, β_3 and β_9.[24] We have also considered spatially and temporally correlated errors following Conley (1999) for OLS estimation and adapted by Colella, Lalive, Sakalli and Thoenig (2018) for panel IV regression.[25] This approach also yields almost uniformly smaller standard errors than our preferred (because conservative) two-way clustering.

5 Baseline results

5.1 Exports and gross lights

Table 3 shows our baseline OLS and IV estimates, taking exports as the trade measure. In columns (1) and (2), we present estimates for on-road cells only (equation 1), while columns (3) and (4) show estimates for on-road and off-road cells combined (equation 2). For both specifications, we show regression estimates without and with instrumenting exports.

[22]We also estimate our baseline IV models using tariffs weighted by pre-sample trade shares and find the results to be very similar.

[23]See Appendix Table A7.

[24]See Appendix Table A8 for a comparison.

[25]For a previous application, see König, Rohner, Thoenig and Zilibotti (2017). We allow for spatial correlation up to 1,000 kilometers, and for serial correlation up to 5 years. See Appendix Table A8.

Table 3: Baseline estimates

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
	Effects on grid cells along road			
Distance from border (in 10km)	0.170***	0.183***	0.171***	0.178***
	(0.030)	(0.058)	(0.028)	(0.065)
Bilateral exports (in logs)	0.058	0.482	0.080	0.556
	(0.146)	(0.519)	(0.155)	(0.513)
Bilateral exports × Distance from border	-0.030***	-0.033**	-0.033***	-0.035**
	(0.010)	(0.016)	(0.010)	(0.016)
	Additional effects on off-road grid cells			
Off-road × Distance from border			-0.156***	-0.144*
			(0.032)	(0.076)
Off-road × Distance from road			-0.009***	-0.008***
			(0.001)	(0.002)
Off-road × Bilateral exports			0.069	0.805
			(0.187)	(1.405)
Off-road × Bilateral exports × Distance from border			0.032***	0.030*
			(0.012)	(0.018)
Off-road × Bilateral exports × Distance from road			-0.002***	-0.002**
			(0.000)	(0.001)
	Control variables			
Altitude (in 100m)	-0.115***	-0.103***	-0.062***	-0.073***
	(0.011)	(0.012)	(0.011)	(0.013)
Slope	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Port closer than next land border (dummy)	1.467***	1.501***	1.452***	1.477***
	(0.353)	(0.300)	(0.271)	(0.260)
Port dummy × Distance from port	-0.144***	-0.110***	-0.136***	-0.130***
	(0.039)	(0.038)	(0.049)	(0.055)
Airport closer than next land border (dummy)	1.162***	1.006***	0.689***	0.668***
	(0.105)	(0.112)	(0.091)	(0.088)
Airport dummy × Distance from airport	-0.049***	-0.034***	-0.030***	-0.027***
	(0.020)	(0.011)	(0.010)	(0.011)
Same ethnicity on both sides of border (dummy)	-0.078	-0.070	-0.065	-0.069
	(0.101)	(0.095)	(0.088)	(0.096)
Off-road cells	NO	NO	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic		15		13
# Clusters	812	812	1,639	1,639
# Observations	113,289	113,289	648,783	648,783

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Our coefficient estimates turn out to be stable across specifications, statistically significant in most instances, and consistent with attenuated light gradients throughout. Our OLS and IV estimates are qualitatively identical.[26] Instrumenting, however, strongly increases the estimated main effect of exports, $\hat{\beta}_2$. We interpret this as reflecting the effect of measurement error biasing these estimates towards zero in the OLS estimations, since tariffs are likely measured more precisely than trade volumes. The control variables affect light intensities in ways

[26]Our instrument is strong. First-stage F-statistics, shown at the bottom of Table 3, are above conventional acceptance thresholds. Appendix Table A8 shows Table 3 with alternative standard error estimates. Appendix Table A9 shows representative first stage results for column (4). Appendix Table A10 shows that instrumenting with tariffs weighted by 1994 trade shares leaves our estimates essentially unchanged.

that correspond to expectations: high-altitude locations are darker, and locations close to ports and airports are brighter.[27] Ethnic homogeneity across borders, however, is not found to affect light intensity statistically significantly.

Our baseline estimates of the main effect of export, $\hat{\beta}_2$, while positive as predicted turn out not to statistically significant. This is largely a result of our demanding fixed-effects specification. When including only road and year fixed effects, these coefficients are estimated much more precisely and with somewhat larger magnitudes.[28]

We find strong evidence of border shadows. Estimated coefficients on the raw distance measure $\hat{\beta}_1$ are significantly positive across all specifications. According to our preferred specification, reported in column (4) of Table 3, economic activity measured through night lights increases by some 18 percent with every 10 kilometers of distance from the border in a hypothetical scenario of zero cross-border trade. For off-road cells, the distance gradient from the border is weaker – about 3 percent per 10 kilometers according to that same specification.

The multiple interaction terms of our regression model do not lend themselves individually to easy interpretation. In Figure 6, we therefore illustrate the border shadow implied by our preferred estimates (Table 3, column 4). 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. We calibrate all variables at the 25th percentile of their sample distribution. We show predicted grid-cell light intensities as a function of the estimated coefficients, with variation across grid cells being determined by the spatially identified parameters $\hat{\beta}_1$, $\hat{\beta}_3$, $\hat{\beta}_4$, $\hat{\beta}_5$, $\hat{\beta}_6$, $\hat{\beta}_8$ and $\hat{\beta}_9$ (equation 2).[29] The shading of the grid cells illustrates predicted light intensities, and predicted values are reported inside each cell.

It is evident from Figure 6 that our estimates imply pronounced border shadows also with trade intensity at the 25th percentile: predicted lights get brighter as one moves away from the border, both on and off the main road. The figure also illustrates how light intensity drops off abruptly as one moves away from the road.

Our second and main result is that the border shadows illustrated in Figure 6 are attenuated by cross-border exports. The interaction coefficient $\hat{\beta}_3$ is statistically significantly negative in all regression specifications. This suggests that export growth leads to stronger increases in lights close to the border than further inland. For example, the estimated coefficient in our preferred specification (Table 3, column 4) implies that the brightening effect of export growth falls by some 3.5 percent with every 10 kilometers of distance from the border.[30]

Our estimates for $\hat{\beta}_2$, while consistently positive, are not statistically significant in our baseline specifications (Table 3). Complementary estimations show that the statistical imprecision of these estimates is due to the inclusion of region-year fixed effects, which assign each

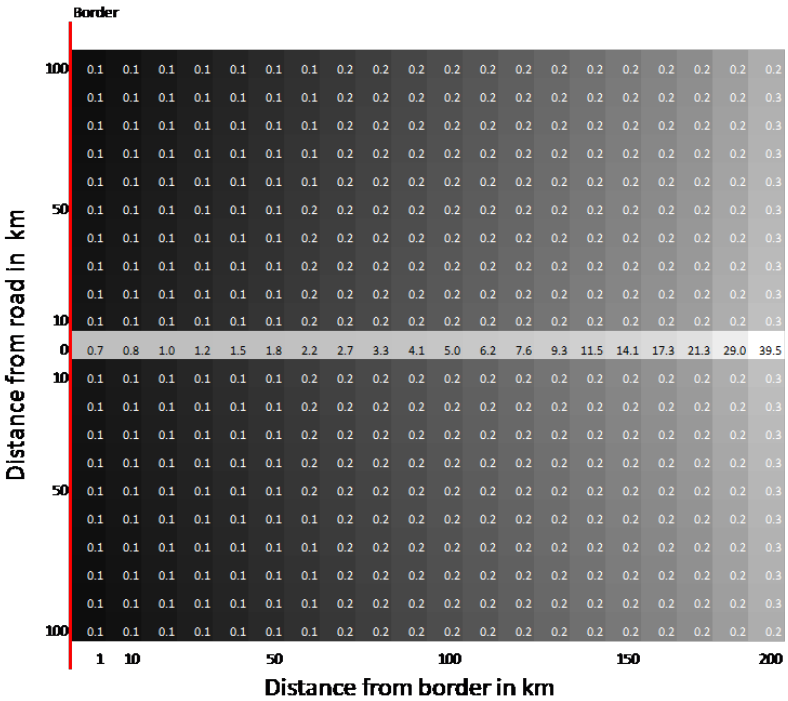
[27] To the extent that bilateral trade is by air or sea, our estimated coefficients $\hat{\beta}_2$ and $\hat{\beta}_3$ would be biased towards zero in the absence of adequate controls, since trade-induced changes in lights might then not correlate with the geography of border-crossing roads.

[28] See columns (1) to (4) of Appendix Table A11. The region-year fixed effects included in our baseline regression model assign each grid cell within a region to the closest neighbor country but do not take into account the distances to other neighbor countries. Hence, even grid cells that are almost equidistant from two different neighbor countries are assigned to a single neighbor country, while in reality they will be affected by trade also with the other neighbor country. This likely biases our estimated effect for $\hat{\beta}_2$ towards zero (see columns (5) to (8) of Appendix Table A11).

[29] 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.

[30] We consider only roads that were already recorded in 1995 (see Appendix A). This if anything works against obtaining significant estimates $\hat{\beta}_2$ and $\hat{\beta}_3$, because new roads constructed in the vicinity of our sample roads would decrease the effects measured along the pre-existing roads.

Figure 6: The predicted border shadow



	1	10				50					100					150				200
100	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
50	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
10	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
0	0.7	0.8	1.0	1.2	1.5	1.8	2.2	2.7	3.3	4.1	5.0	6.2	7.6	9.3	11.5	14.1	17.3	21.3	29.0	39.5
10	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
50	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3
100	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

Note: The graph shows predicted light intensities based on a specification featuring road fixed effects, region-year fixed effects, neighbor-country-year fixed effects, all control variables and exports instrumented with tariffs (Table 3, column 4), with exports set to the value of the 25th percentile in our data. Darker colors symbolize lower light intensity.

grid cell within a region to the closest neighbor country but do not take into account distances to other neighbor countries.[31] Hence, grid cells located at similar distances from different borders are assigned to only one neighbor country, while in reality trade with another neighbor (or even neighbors) might be similarly important. This biases our estimated coefficient for $\hat{\beta}_2$ towards zero.

We again provide a graphical illustration of the combined effects of our estimates. Figure 7 is constructed analogously to Figure 6 but rather than showing predicted light intensities for a given level of exports we show predicted percentage changes in light intensities for a doubling of exports, at the mean values of the remaining variables.[32] It appears clearly in Figure 7 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 off the main roads but close to them, implying some dispersion away from narrow road corridors that attenuates the steep drop-off in activity evident in Figure 6.

In summary, increased trade attracts 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.[33]

5.2 Lights per capita

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 order to address this question, we combine the lights data with the Gridded Population of the World dataset published by the Earth Institute of Columbia University, which are available at the same 10×10 kilometer resolution as the one we choose for our analyses based on lights only (see Appendix A for details).

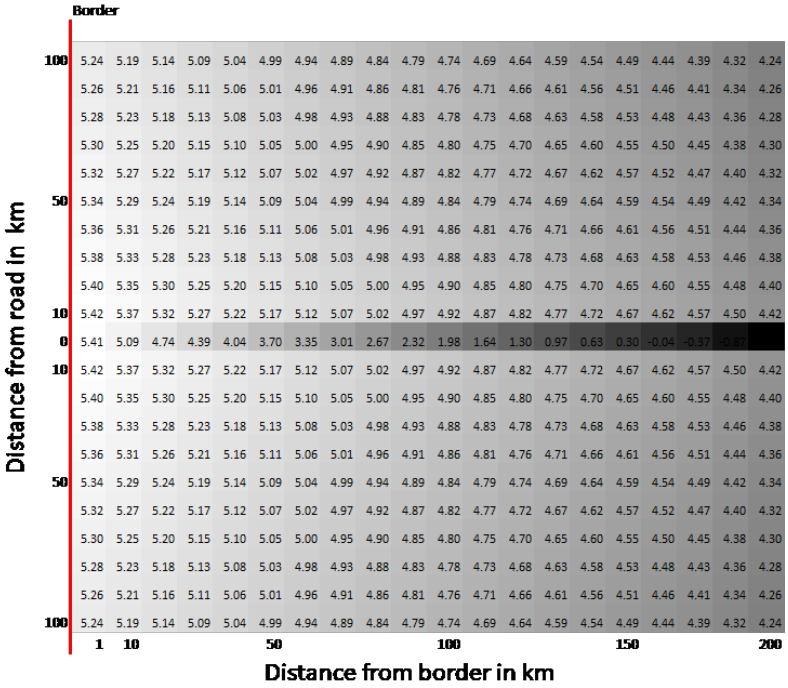
In Table 4, we show estimates of our baseline models (2) with lights per capita and population as the dependent variable. By construction, these estimates add up to the raw lights estimates reported in columns (3) and (4) of Table 3. The disaggregated estimates suggest that border shadows reflect both lower income (proxied by lights) and lower population density in border regions. The estimated gradients $\hat{\beta}_1$ in per capita and population terms are of similar magnitude. Regarding the effect of trade, our results of Table 4 also imply that, within our 200-kilometer border regions, increased exports raise both population and incomes.

[31]See Appendix Table A11. Columns (1) to (4) show results for a within-road estimation including year fixed-effects, but not controlling for region-year and neighbor-year fixed effects. In these specifications, $\hat{\beta}_2$ is consistently estimated as positive and statistically significant. However, including neighbor-year fixed effects but no road fixed effects in columns (5) to (8), leads to statistically insignificant estimates of $\hat{\beta}_2$, like in our baseline result.

[32]For our graphical illustration we set exports to the value at the 25th percentile, because when we set it at the mean value, the off-road border shadow no longer emerges.

[33]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.

Figure 7: 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 (i.e. starting from the values presented in Figure 6, based on a specification featuring road fixed effects, region-year fixed effects, neighbor-year fixed effects, all control variables and exports instrumented with tariffs (Table 3, column 4)). Darker colors symbolize lower light intensity.

Table 4: Baseline effects for light intensity per capita and population

Dependent variable:	Lights per capita (logs)		Population (logs)	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Distance from border (in 10km)	0.101***	0.097***	0.070***	0.081***
	(0.033)	(0.036)	(0.019)	(0.023)
Bilateral exports (in logs)	-0.039	0.395**	0.119	0.161
	(0.047)	(0.205)	(0.093)	(0.099)
Bilateral exports × Distance from border	-0.011***	-0.011***	-0.022***	-0.024**
	(0.002)	(0.003)	(0.007)	(0.014)
Off-road cells	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
Kleibergen-Paap F statistic		13		13
# Clusters	1,639	1,639	1,639	1,639
# Observations	648,787	648,787	648,787	648,787

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

5.3 Imports

Up to now, we have defined trade T_{ct} 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'.[34] Results are reported in Table 5, with corresponding estimates for the export specification shown again for ease of comparison.

Table 5: Imports

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
Distance from border (in 10km)	0.171***	0.178***	0.161***	0.166***
	(0.028)	(0.065)	(0.029)	(0.066)
		Effects of exports		
Bilateral exports (in logs)	0.080	0.556		
	(0.155)	(0.513)		
Bilateral exports × Distance from border	-0.033***	-0.035**		
	(0.010)	(0.016)		
		Effects of imports		
Bilateral imports (in logs)			0.071	0.451
			(0.052)	(0.430)
Bilateral imports × Distance from border			-0.019*	-0.016*
			(0.009)	(0.009)
Off-road cells	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
Kleibergen-Paap F statistic		13		12
# Clusters	1,639	1,671	1,429	1,429
# Observations	648,787	648,787	637,029	637,029

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Not surprisingly, we find the coefficients capturing the implied border shadow at zero trade ($\hat{\beta}_1$) to be virtually unchanged. However, both the effect of trade on economic activity at all distances from the border ($\hat{\beta}_2$) and the effect on the gradient from the border ($\hat{\beta}_3$) are smaller in size and less precisely estimated for imports than for exports.[35]

The liberalization of imports thus has qualitatively comparable effects on the economic geography of border regions, though with somewhat lesser intensity.

[34] 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.

[35] When we consider exports and imports simultaneously, we also find the two trade measures to yield the same coefficient signs. However, given the strong collinearity of the two variables, inference – both for OLS and IV – becomes very imprecise.

5.4 Robustness

One evidently arbitrary choice underlying our baseline specifications concerns the width of the distance band around the border. We have run extensive sensitivity tests on alternatives to our baseline 200-kilometer distance cut-off, and found the qualitative patterns to be robust: border shadows are strong when trade intensities are low, and they are significantly reduced by trade liberalization.[36] The only noticeable irregularity we observe is that the main effect on distance, $\hat{\beta}_1$, more than doubles when we reduce the distance cut-off to 50 kilometers – an observation that is however entirely consistent with zero-trade average light intensity being lower the closer one gets to the border.

We also explored the sensitivity of our results to the consideration of data for 2013, the last year for which comparable night-light measurements are available. Our estimates remain virtually unchanged.[37]

We have investigated the effect on our estimates of four further considerations.

First, we drop grid cells located on border crossing points. This is to purge our estimations from any effects that might be due merely to greater activity at customs posts associated with export growth. It turns out that any such effects are very small. The main coefficient of distance from border ($\hat{\beta}_1$) is slightly reduced when not considering border grid cells themselves, but the effects related to trade are virtually indistinguishable.[38]

Second, we consider the issue of "overglow", whereby inaccuracies in the spatial precision of light measurement by satellites leads to the attribution of light emitted in one cell to neighboring cells. We follow Pinkovskiy (2017), who proposes a correction based on a measured spatial autoregression term. Applying this correction leaves our estimates virtually unaffected.[39]

Third, we exclude small countries of an area less than that of a circle of 400 kilometers in diameter, showing that constraints on the size of our border buffers do not seem to be a major issue. This reduces the number of observations by some 10% and does not significantly alter any estimation results.[40]

Fourth, we estimate our regression model on landlocked countries only, thus dropping all observations where some bilateral shipments could travel by sea and "interior" regions include ocean coasts. This shrinks the size of the sample by almost 90%, but the qualitative results are again identical to the baseline estimates of Table 3. The estimated main effects $\hat{\beta}_1$, capturing the implied border shadow at zero trade, however are two to three times as large as in the full sample, consistent with the view that land borders matter more in the absence of access to ocean transport.[41]

Finally, as a complementary and more demanding estimation approach again, we estimate a version of our baseline equation (1) in which we consider grid-cell fixed effects instead of road fixed effects.[42] In this variant of the model, identification is attained solely from intertemporal variation. Time-invariant variables drop out, which means that we cannot in this specification estimate the border shadow for a given level of trade. We can, however, assess the impact of a growth in exports. Our estimates confirm the dispersing effect of

[36]See Appendix Table A6, where we report estimations for 150, 100 and 50 kilometer distance cutoffs.

[37]See Appendix Table A12.

[38]See Appendix Table A4.

[39]It is not surprising that this issue seems of little concern in our context whereas is matters significantly for Pinkovskiy (2017), because that analysis is focused on sharp discontinuities at borders whereas ours focuses on rather wide border-region bands inside each country (see columns (3) and (4) of Appendix Table A13).

[40]See column (3) of Appendix Table A13.

[41]See column (4) of Appendix Table A13.

[42]See Appendix Table A14.

increased trade: export growth is again found to have the strongest brightening effect on grid cells located close to the border and to the main road.

5.5 EU enlargement as an event study

In a further attempt at ascertaining the causal nature and pervasiveness of our detected effects, we focus on the two most recent enlargements of the European Union (EU) as an event study. The timing of accession to the EU is arguably exogenous to the economic fortunes of specific border regions. And even though EU-related trade liberalization has always been a gradual process of which accession was only the culminating conclusion, there is evidence that accession provides discrete additional impetus to trade flows between incumbents and accession countries.[43]

We therefore limit the sample to countries that joined the EU either in 2004 or in 2007, considering the effect on the side of the border that was previously not in the EU.[44] In this setting, our trade variable is a dummy that takes the value of 1 if the border between the two countries belongs to the European Union in year t. As a complementary exercise, we run "placebo" regressions for the same sample countries but considering their borders with non-EU countries. So, for example, the dummy for Poland's border with Germany switches from 0 to 1 between 2000 and 2005 in the accession regressions; whereas in the placebo regression we switch Poland's border with Ukraine from 0 to 1 in that same time interval, even though the institutional setting for Poland-Ukraine trade remained essentially unchanged over that period.

Table 6: Results for countries that accessed the EU in 2004 and 2007 (borders to EU-members)

Dependent variable: Average light intensity (logs)		
	(1)	(2)
	OLS	OLS
Treatment	Accession borders	Placebo borders
Distance from border (in 10km)	0.638***	0.298***
	(0.088)	(0.107)
Border post-EU accession (dummy)	0.591***	0.149
	(0.161)	(0.123)
Border post-EU accession × Distance from border	-0.410***	-0.171
	(0.112)	(0.155)
Off-road cells	YES	YES
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
# Clusters	144	240
# Observations	20,708	38,616

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

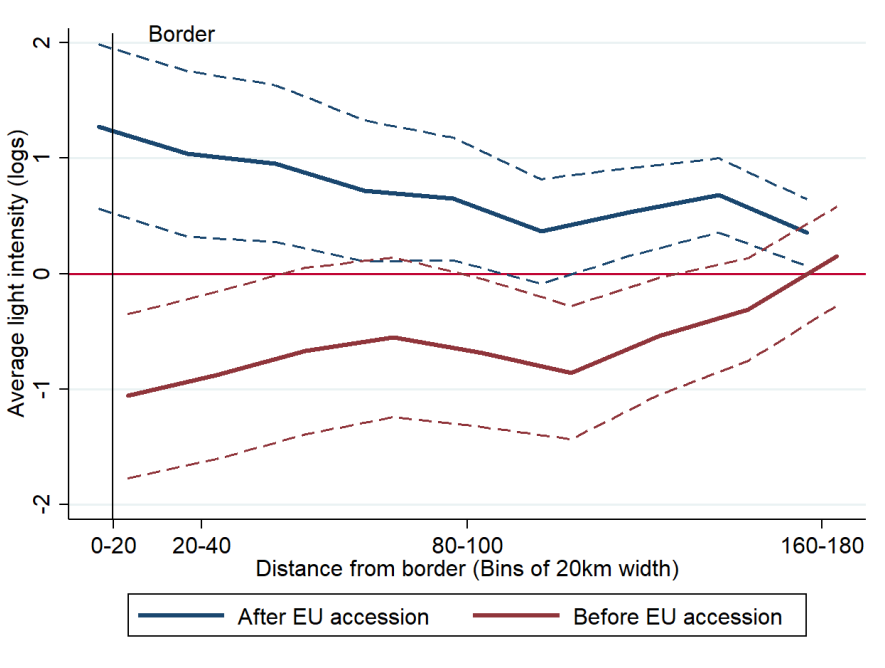
Two-way clustered standard errors at road and country-pair-year level in parentheses.

Once again, we find strong evidence of border shadows being attenuated by trade liberalization. The coefficients in the first two columns of Table 6 are all signed consistently with our prior findings and are statistically significant. Border shadows are found to be very pronounced before accession, with night lights increasing by some 64 percent with every 10 kilometers of distance from the border – an effect that is almost four times as strong as the no-trade lights gradient implied by our world-wide baseline estimates of Table 3. This illustrates

[43]See e.g. Cheptea (2013).

[44]The 2004 accession countries were Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovenia and Slovakia. The 2007 accession countries were Bulgaria and Romania. Because they are islands, Cyprus and Malta do not inform our estimates.

Figure 8: The effect of accessing the European Union



Note: The graph represents the point estimates for a within-road regression according to equation (1), where distance is expressed as a set of dummy variables for bins of 20 km width. The sample is split into "before EU accession" (red line) "after EU accession" (blue line) years.

the activity-depressing impact of the Iron Curtain. Once a border becomes part of the EU, however, the gradient of lights within the 200 kilometer border region disappears altogether, and the border region on average becomes some 59 percent brighter than before accession. We illustrate these effects in Figure 8, which visualizes the stark reversal in the fortunes of border regions after accession to the EU.

The placebo regressions reported in the right half of Table 6 show that border shadows also exist in the east of the accession countries, but they were not discernibly reduced after EU accession. This further supports our interpretation of the accession effects as being caused by improved cross-border market access made possible by EU enlargement. We do not find evidence of reduced activity in eastern border regions, which suggests that growth in regions bordering the EU did not come at the expense of growth in regions bordering non-EU countries.

6 Extensions

6.1 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 on-road baseline model (1) 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 36 advanced and 102 developing economies.

Table 7: Developing and advanced economies

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
	Effects in developing economies	
Distance from border (in 10km)	0.131***	0.118***
	(0.024)	(0.025)
Bilateral exports (in logs)	0.193	0.343
	(0.034)	(0.079)
Bilateral exports × Distance from border	-0.021***	-0.014***
	(0.005)	(0.004)
	Additional effects in advanced economies	
Advanced economy (dummy) × Distance from border	0.052***	0.078***
	(0.016)	(0.024)
Advanced economy × Bilateral exports	0.112***	0.200***
	(0.031)	(0.058)
Advanced economy (dummy) × Distance from border × Bilateral exports	-0.015***	-0.029***
	(0.004)	(0.009)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		13
# Clusters	812	812
# Observations	113,289	113,289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Qualitatively, our main results hold for both subsets of countries: locations close to borders are darker, *ceteris paribus*, but this spatial light gradient flattens as bilateral exports grow. The coefficients in the lower panel of Table 7 suggest that these effects are significantly stronger in advanced economies.[45]

We should however interpret this apparent difference with care, as the weaker 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 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 therefore be interpreted with caution, our results strongly suggest that exports reduce border shadows in both advanced and developing economies.

In Table 8, we subdivide the world further, showing estimates of the on-road baseline model (2) individually by continent. Our world-wide results turn out to be driven by African, Asian and European countries. Restricting the sample to each of these three continents in turn leads to qualitatively similar results. Given that these continents contain some 56 percent of our total number of observations and 123 of our 138 sample countries, it is unsurprising that they dominate our overall estimates.

Our central insights, however, do not seem to generalize readily to the Americas. In Latin

[45] Advanced economies also exhibit stronger measured trade effects when we estimate interaction models with continuous measures of per-capita income, be it in 1990 terms (Appendix Table A15) or in 2015 terms (Appendix Table A16).

Table 8: Effects by continent

Dependent variable: Average light intensity (logs)					
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Continent	Africa	Asia	Europe	Latin America	North America
Distance from border (in 10km)	0.134***	0.061*	0.194***	0.012	-0.108***
	(0.038)	(0.036)	(0.052)	(0.035)	(0.036)
Bilateral exports (in logs)	0.339*	0.342	0.441*	0.111	0.405
	(0.180)	(0.241)	(0.241)	(0.201)	(0.501)
Bilateral exports × Distance from border	-0.035***	-0.033***	-0.052***	-0.024	0.025***
	(0.010)	(0.011)	(0.014)	(0.021)	(0.011)
Off-road cells	YES	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES	YES
Kleibergen-Paap F statistic	12	11	10	3	13
# Countries	42	43	38	13	2
# Clusters	291	132	527	447	242
# Observations	53,207	168,015	139,716	155,426	132,586

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

America, the estimated border-shadow-reducing effects of exports are consistent with those we detect elsewhere, but they are not statistically significant. Moreover, there is no evidence of border shadows in a hypothetical zero-export scenario, the main effect of distance, $\hat{\beta}_1$, being indistinguishable from zero. In North America, border regions are brighter, *ceteris paribus* than interior regions. This is no doubt due to the continent's particular geography, with many urban centers clustered along the U.S. borders.

6.2 Cities

So far, we have controlled for the most important features of topography and for proximity to ports and airports, but we otherwise abstracted from within-country economic geography. Even conditional on these sources of spatial heterogeneity, however, locations may be unequally positioned to benefit from opportunities for cross-border trade. One evident source of heterogeneity is urbanization: cities are likely to be affected differently from rural locations. Such differences could arise for multiple reasons, including different sectoral specialization, different skill abundance, different availability of trading infrastructure, and agglomeration effects. Existing empirical studies seem to support the hypothesis that access to cross-border trade favors rural regions and smaller cities more than large cities, but these studies are all based on individual countries.[46]

In a first step towards investigating this issue, we distinguish "urban" roads from "rural" roads. Roads are defined as urban if anywhere within 200 kilometers from the border they reach a city with a population of at least 500,000.[47] For urban roads, we do not consider segments that lie between the first city reached when travelling inland from the border and

[46]Redding and Sturm (2008) show that population growth of smaller intra-German border towns suffered relatively more from Cold War partition than population growth of larger towns. Baum-Snow *et al.* (2019) find that population and GDP of non-primate Chinese prefectures grew more strongly than those of primate prefectures as a result of improved access to major sea ports.

[47]Data on the location of cities are taken from Natural Earth. Appendix Table A17 shows results based on a population cut-off of 100,000. The qualitative results are very similar.

the 200 kilometer cut-off, but the grid cells covering the city itself are included. According to this definition, 46% of sample grid cells belong to urban roads. Among urban roads, the average distance from the border to the nearest city is 47 kilometers.

We estimate on-road-cell models analogous to equation (1), and we interact the distance and export variables with a dummy for urban roads.[48]

Table 9: Urban and rural roads

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
	Effects on rural roads	
Distance from border (in 10km)	0.121***	0.103***
	(0.030)	(0.035)
Bilateral exports (in logs)	0.274	0.360
	(0.189)	(0.263)
Bilateral exports × Distance from border	-0.015***	-0.017***
	(0.005)	(0.006)
	Additional effects on urban roads	
Road leading to city >500k (dummy) × Distance from border	0.079***	0.116**
	(0.033)	(0.054)
Road leading to city >500k × Bilateral exports	0.104**	0.166***
	(0.050)	(0.051)
Road leading to city >500k × Distance from border × Bilateral exports	-0.039***	-0.048***
	(0.010)	(0.016)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		12
# Clusters	776	776
# Observations	108,019	108,019

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table 9 reports our estimation results. Unsurprisingly, urban roads are found to be brighter on average than rural roads, and they have a steeper light gradient. Our main results holds both for urban and rural roads: exports reduce the gradient of lights. This effect is significantly more pronounced for urban roads, however. This suggests that border locations stand to benefit more from trade if they are close to a city in their own country. Consistent with this, the effect of exports on lights at the border is about twice as strong for urban roads as for rural roads. These results imply that urban border regions stand to benefit comparatively more from trade liberalization than rural border regions, a result somewhat at odds with previous empirical findings.

In a second step, we consider city locations on the opposite side of the border. This allows us to account for heterogeneity in treatment intensity along a given border segment: a given change in trade openness toward a neighbor country is likely to have a stronger impact in the vicinity of border crossings situated close to a center of economic activity in that neighbor country than in the vicinity of border crossings far away from any neighbor-country economic hub.[49] Our findings conform with expectations: the positive effect of export expansion is greater for border locations close to a city on the other side of the border, and this is true for

[48]This is equivalent to estimating equation (2) with a binary variable that is set to one for all grid cells that are located on urban roads instead of the binary variable Off_i.

[49]This is consistent with the simulations reported by Redding and Rossi-Hansberg (2017, p. 42), which suggest that "(t)he areas that benefit the most are the ones close to but on the opposite side of the border from the large cities".

both urban and rural roads (with respect to city location on the own side of the border).[50]

6.3 A mechanism: increased border-region production

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 25 different crops at a resolution of 10×10 kilometers. This information allows us to establish the main agricultural product for each 10×10 kilometer grid cell as the crop that occupies the biggest share of land.[51] Additionally, we compute the share of total land (not just arable land) that is used to grow the dominant crop of a given grid cell, which we then use to weight grid cells according to the importance of their main crop.[52]

We estimate two variants of equation (1). In columns (1) and (2) of Table 10, we present estimates of equation (1) using exports of the major crop grown in cell i to neighbor country c' as the trade variable, using neighbor-country c''s tariff on this product and the world price of the respective crop as instruments. In columns (3) and (4), we report specifications with the trade variable defined as overall exports instrumented with average tariffs. Columns (3) and (4) of Table 10 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.[53]

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 10 shows that both our estimated main effect of exports and the interaction effect with distance are noticeably larger when we focus on exports of border regions' dominant crops than when we consider overall trade.

6.4 Trade and border-region conflict

In a final extension, we tentatively explore the hypothesis that cross-border trade can mitigate violent conflict in border regions. To this end, we consider a geo-referenced measure of conflict intensity as an alternative dependent variable.

[50] See Appendix Tables A18 and A19.

[51] For a list of crops in the sample, see Appendix Table A22. See Appendix A for details on the data.

[52] This is not an essential procedure, our results turning out to be similar in unweighted regressions.

[53] The underlying dataset concerning crops has less than 20% of land classified as "cropland" for the majority of countries (a distinction is made between cropland and pasture). Since we use only information on crops, the number of observations in this exercise shrinks to about a quarter of our baseline sample. Note that in this specification we can also draw on identifying variation across different crops within a given road and year.

Table 10: Trade in local crops

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
Distance from border (in 10km)	0.162***	0.199***	0.158***	0.202***
	(0.045)	(0.065)	(0.059)	(0.075)
	Effects of exporting main crop			
Bilateral crop exports (in logs)	0.404**	0.557**		
	(0.199)	(0.275)		
Bilateral crop exports × Distance from border	-0.055***	-0.091***		
	(0.024)	(0.035)		
	Effects of overall exports			
Bilateral exports (in logs)			0.152	0.236
			(0.119)	(0.175)
Bilateral exports × Distance from border			-0.021	-0.026
			(0.019)	(0.023)
Off-road cells	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
Kleibergen-Paap F statistic		13		12
# Clusters	417	417	417	417
# Observations	159,982	159,982	159,982	159,982

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

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Note: Cells are weighted according to the share of land used to grow the major agricultural crop.

Data on conflict are publicly available through the Armed Conflict Location & Event Data Project (ACLED). During our sample period, the data are available for Africa only.[54] The data report the geo-coded location of events of armed conflict, the type of event (riots, violence against civilians and different forms of battle), and the number of casualties.

We aggregate this information to 20 × 20 kilometer grid cells, in order to minimize the occurrence of zeros. The dependent variable is the number of events per grid cell in a given year. We again consider 200 kilometer distance bands around land borders.

Table 11 reports the results for estimations using OLS, IV, Poisson and IV Poisson estimators. While we do not observe a "border shadow" in terms of conflict, our estimates consistently suggests that cross-border trade reduces the incidence of violent conflict in border regions. A doubling of cross-border trade is associated with a 4 to 6 percent reduction in conflict incidents within border regions. While imprecisely estimated, our coefficients on the interaction variable are once again positive, suggesting that within the 200-kilometer border region any conflict-reducing effect of increased trade will be stronger in locations close to the border.

7 Conclusion

Our estimates based on world-wide spatially disaggregated data suggest that trade facilitation 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

[54]Data for Africa are available from 1997 onwards, whereas data for the Middle East and South and East Asia are available, respectively, from 2017 and 2015 onwards.

Table 11: Conflict estimates

Dependent variable: Number of events	Logs + 1		Raw counts	
	(1) OLS	(2) IV	(3) Poisson	(4) IV-Poisson
Distance from border (in 20km)	-0.0002	-0.0004	-0.0013	-0.0017
	(0.0003)	(0.0004)	(0.0011)	(0.0272)
Exports to neighbor country (in logs)	-0.0409**	-0.0356**	-0.0552**	-0.0604*
	(0.0188)	(0.0167)	(0.0224)	(0.0341)
Exports to neighbor country × Distance from border (in 20km)	0.0047	0.0052	0.0093	0.0104
	(0.0150)	(0.0224)	(0.0202)	(0.0288)
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
Kleibergen-Paap F statistic		12		12
# Clusters	102	102	102	102
# Observations	9,981	9,981	9,981	9,981

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

equalizing effect of international trade. The effect emerges very consistently irrespective of how we cut the data: it applies to both developing and advanced economies, and to both rural and urban regions. We also find that border regions benefit in gross terms as well as in per-capita terms, suggesting that trade expansion boosts both the populations and the incomes of border regions. Based on detailed information on agricultural production and trade, we moreover establish that trade-related development of border regions is significantly driven by local export-oriented production.

Our results also show that land borders are, in themselves, factors of remoteness. This is a striking result in view of the finding 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.[55] Another limitation is that our approach cannot capture long-term effects on economic geographies: we observe at most an eighteen-year data span, and we take spatial urbanization patterns and local sectoral specialization as exogenously given.

[55]We note, though, that quantitative economic geography models featuring imperfect intra-national labor mobility, local changes in population, real wages and welfare are strongly correlated (Redding, 2016).

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A Data sources

Our data on *night lights* are described in Section 3.1.

Data on *population* density are taken from the Gridded Population of the World dataset version 4 published by the Earth Institute of Columbia University. The dataset contains globally consistent population information by grid cell, drawn from national censuses for varying subnational units (municipalities, census tracts, etc.). The finest available grid-cell resolution is 2.5 arc-minutes, or around 5 kilometers at the equator. The underlying census data cover more than 300,000 national and sub-national administrative units worldwide. Within each of these subnational units, population is distributed across grid cells using an algorithm that takes into account characteristics such as the location of cities and lakes, and the average population density of rural and urban areas in the relevant subnational units. For details on the computation of grid cell-level population densities, see Balk, Deichmann and Yetman (2001).

Since the Gridded Population data are available for the years 1995, 2000, 2005 and 2010, we also use the lights data for those years throughout this paper, although in some analyses we also consider lights for 2013.

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.

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 the location of *cities* are taken from Natural Earth. Data on *roads* are obtained from the ESRI Roads and Highways dataset. Road locations are taken as recorded in the 1995 version of the dataset. The 2010 dataset contains 7% more border crossing roads than the 1995 dataset, but it is not clear whether these represent new roads, upgraded roads, or roads that simply were not recorded in the 1995 data. To avoid problems of attributing light properly to a road in different years, we focus our analysis on roads that were recorded at the beginning of our observation period and follow them through time.

We also considier a number of control variables.

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 and the Emergency and Preparedness Geospatial Information Unit at the World Food Program (WFP). Only airports that appear in both datasets are kept.

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.

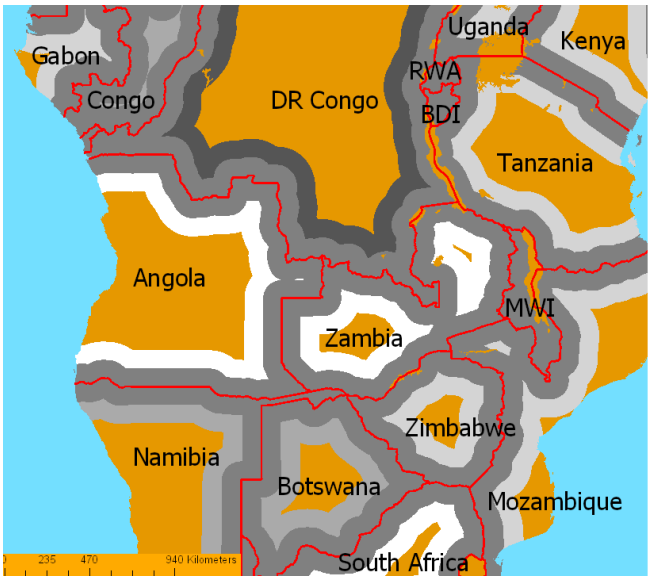
Data on the location of *ethnic groups* are taken from the Geo-referencing of Ethnic Groups (GREG) dataset compiled by Weidmann, Rød and Cederman (2010). The GREG data contain global polygon information on the location of ethnic groups. The size of the polygons ranges from 0.6 to 6,954,564 square kilometers.The main source underlying this dataset is the *Atlas Narodov Mira* (Bruk and Apenchenko, 1964), consisting of 57 ethnographic maps drawn from (1) ethnographic and geographic maps assembled by the Institute of Ethnography at the USSR Academy of Sciences, (2) population census data, and (3) ethnographic publications of government agencies, covering all regions of the world at various scales. Despite the data having been collected in the early 1960s, Weidmann *et al.* (2010, p. 496) argue that "ethnic settlement patterns exhibit a lot of inertia, so that it is plausible to also use the GREG data as the basis for measuring ethnic geography in recent times".

Finally, worldwide data on harvested areas of 175 *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. Appendix Table A22 lists the crops considered and provides summary statistics. The dataset is constructed from two different satellite datasets on land cover and then combined with data from agricultural censuses and FAO data.

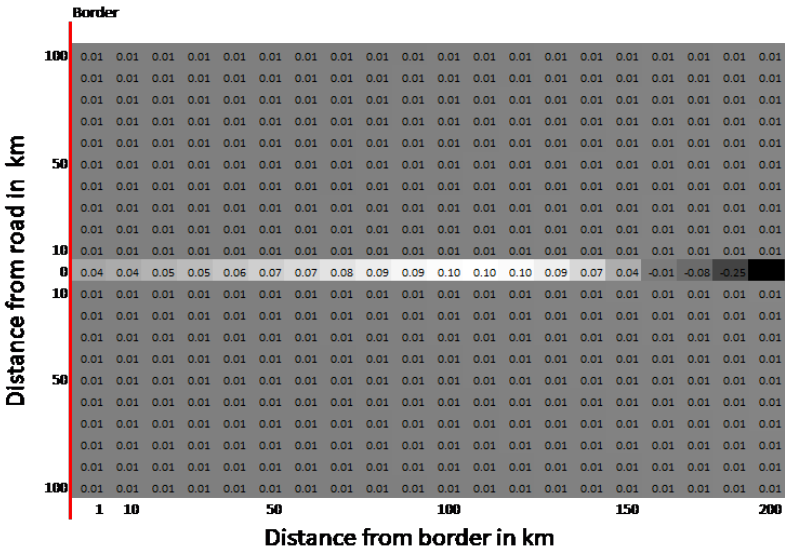
B Appendix figures and tables

Figure A1: Border shadows in Sub-Saharan Africa



Note: The map illustrates average light intensity along roads within two bands of 100km from land borders. The shading of the 100-200km band represents relative light intensity with respect to light intensity in the 0-100km band. White or light gray 100-200km bands are consistent withour baseline definition of border shadows, not conditioned on any covariates.

Figure A2: Predicted absolute change in light intensity associated with a doubling of exports



Note: The graph shows predicted absolute changes in light intensity after a doubling of 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 6, based on a specification featuring road fixed effects, year fixed effects, all control variables and exports instrumented with tariffs (Table 3, column 4). Darker colors symbolize lower light growth.

Table A1: Summary statistics: baseline sample (on-road and off-road grid cells)

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	3.93	8.93	0	63	649,109
Distance from border	92.14	48.52	0.00	200	649,109
Total exports to neighbor country (in 100 mio US dollar)	324.79	652.93	0.00	2131.69	649,109
Simple average applied tariff rate	4.33	6.96	0	104.34	649,109
Population density (people/km^2)	32.51	255.11	0	31,735	649,109
Regional trade agreement dummy	0.67	0.47	0	1	649,109
Altitude	766.98	886.92	-405	6659	649,109
Same ethnicity dummy	0.06	0.20	0	1	649,109
Port dummy	0.03	0.18	0	1	649,109
Airport dummy	0.25	0.43	0	1	649,109
Distance from port (if port dummy = 1)	72.69	47.50	1.88	189.86	22,105
Distance from airport (if airport dummy = 1)	62.21	46.14	1.09	199.34	168,362
Dummy for road leading to city >100,000 inhabitants	0.35	0.48	0	1	649,109
Dummy for road leading to city >500,000 inhabitants	0.02	0.15	0	1	649,109
Dummy for light = 0	0.53	0.35	0	1	649,109
Average light intensity at 0 km distance	2.97				
Average light intensity at 100 km distance	3.41				
Average light intensity at 200 km distance	4.75				

Table A2: Summary statistics: on-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	10.86	11.81	0	63	113,512
Distance from border	76.21	40.75	0.00	200	113,512
Total exports to neighbor country (in 100 mio US dollar)	378.21	681.84	0.00	2131.69	113,512
Simple average applied tariff rate	3.72	6.56	0	104.34	113,512
Population density (people/km^2)	130.45	471.89	0	31,735	113,512
Regional trade agreement dummy	0.69	0.46	0	1	113,512
Altitude	580.58	703.14	-405	5540	113,512
Same ethnicity dummy	0.03	0.17	0	1	113,512
Port dummy	0.04	0.19	0	1	113,512
Airport dummy	0.28	0.45	0	1	113,512
Distance from port (if port dummy = 1)	56.38	41.76	1.88	189.86	22,105
Distance from airport (if airport dummy = 1)	50.43	39.60	1.09	199.34	168,362
Dummy for road leading to city >100,000 inhabitants	0.37	0.48	0	1	113,512
Dummy for road leading to city >500,000 inhabitants	0.05	0.21	0	1	113,512
Dummy for light = 0	0.19	0.47	0	1	113,512
Average light intensity at 0 km distance	8.33				
Average light intensity at 100 km distance	10.06				
Average light intensity at 200 km distance	11.54				
Number of conflict events (20 $\times$ 20 km cells, Africa only)	0.53	4.28	0	109	9,981
Conflict fatalities (20 $\times$ 20 km cells, Africa only)	5.95	58.19	0	2769	9,981

Table A3: Summary statistics: off-road grid cells

Variable	Mean	Std. Dev.	Min.	Max.	N
Average light intensity	1.23	3.70	0	37.8	535,597
Distance from border	95.52	43.88	0.00	200	535,597
Total exports to neighbor country (in 100 mio US dollar)	314.30	646.59	0.00	2131.69	535,597
Simple average applied tariff rate	4.46	7.04	0	104.34	535,597
Population density (people/km^2)	11.75	88.12	0	9,190	535,597
Regional trade agreement dummy	0.66	0.47	0	1	535,597
Altitude	806.49	916.32	-405	6659	535,597
Same ethnicity dummy	0.09	0.22	0	1	535,597
Port dummy	0.03	0.17	0	1	535,597
Airport dummy	0.25	0.43	0	1	535,597
Distance from port (if port dummy = 1)	76.15	47.99	1.88	189.86	17,881
Distance from airport (if airport dummy = 1)	64.96	47.11	1.09	199.34	136,521
Dummy for road leading to city >100,000 inhabitants	0.34	0.48	0	1	535,597
Dummy for road leading to city >500,000 inhabitants	0.02	0.13	0	1	535,597
Dummy for light = 0	0.60	0.36	0	1	535,597
Average light intensity at 0 km distance	0.89				
Average light intensity at 100 km distance	1.09				
Average light intensity at 200 km distance	1.68				

Table A4: Baseline estimates, excluding border-crossing grid cells

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
	Effects on grid cells along road			
Distance from border (in 10km)	0.179***	0.188***	0.185***	0.193***
	(0.029)	(0.055)	(0.028)	(0.063)
Bilateral exports (in logs)	0.060	0.475	0.075	0.541
	(0.138)	(0.503)	(0.142)	(0.500)
Bilateral exports × Distance from border	-0.029***	-0.031**	-0.031***	-0.033**
	(0.010)	(0.015)	(0.011)	(0.014)
	Additional effects on off-road grid cells			
Off-road × Distance from border			-0.157***	-0.147*
			(0.032)	(0.077)
Off-road × Distance from road			-0.010***	-0.009***
			(0.002)	(0.003)
Off-road × Bilateral exports			0.073	0.800
			(0.180)	(1.382)
Off-road × Bilateral exports × Distance from border			0.033***	0.032*
			(0.013)	(0.018)
Off-road × Bilateral exports × Distance from road			-0.002***	-0.002**
			(0.000)	(0.001)
Off-road cells	NO	NO	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic		15		13
# Clusters	812	812	1,639	1,639
# Observations	103,674	103,674	598,113	598,113

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A5: Polynomial regression

Dependent variable: Average light intensity (logs)	(1) OLS	(2) OLS
Distance from border (in 10km)	0.228***	0.221***
	(0.055)	(0.086)
Distance from border (in 10km) squared	-0.006	-0.003
	(0.005)	(0.006)
Bilateral exports (in logs)	0.066	0.433
	(0.142)	(0.513)
Bilateral exports × distance to border	-0.027***	-0.029***
	(0.008)	(0.011)
Bilateral exports × Distance from border squared	-0.001	-0.001
	(0.001)	(0.002)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
First-stage F statistic		11
# Clusters	812	812
# Observations	113,289	113,289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A6: Sensitivity to different border distance cutoffs

Dependent variable: Average light intensity (logs)	(1) IV	(2) IV	(3) IV	(4) IV
Maximum distance from border (in km)	200	150	100	50
Distance from border (in 10km)	0.178***	0.195***	0.206**	0.489***
	(0.065)	(0.070)	(0.072)	(0.125)
Bilateral exports (in logs)	0.556	0.450	0.386*	0.334**
	(0.513)	(0.364)	(0.219)	(0.164)
Bilateral exports × Distance from border	-0.035***	-0.025***	-0.020**	-0.029*
	(0.013)	(0.008)	(0.010)	(0.016)
Off-road cells	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic	13	13	13	12
# Clusters	1,639	1,639	1,639	1,608
# Observations	648,783	633,105	596,279	491,880

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A7: Differences in pre-sample light intensity

	Mean	Standard Deviation	Observations	t statistic	p value
Above median trade	3.8346	9.00	319,332		
Below median trade	3.8059	8.91	329,777		
Difference	0.0287	0.022		1.29	0.1967

Difference in 1992 light intensity between below and above mean trade border regions. Regions are grouped as follows: first, we compute time-averaged exports for each region. Then, regions are labelled as above (below) median trade if its median trade over time is higher (lower) than the median across all regions.

Table A8: Baseline estimates with different ways of error clustering

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
	Effects on grid cells along road			
Distance from border (in 10km)	0.170	0.183	0.171	0.178
	(0.030)	(0.058)	(0.028)	(0.065)
	[0.026]	[0.044]	[0.023]	[0.057]
	{0.021}	{0.036}	{0.018}	{0.042}
Bilateral exports (in logs)	0.058	0.482	0.080	0.556
	(0.146)	(0.519)	(0.155)	(0.513)
	[0.121]	[0.402]	[0.134]	[0.382]
	{0.081}	{0.299}	{0.095}	{0.277}
Bilateral exports × Distance from border	-0.030	-0.033	-0.033	-0.035
	(0.010)	(0.016)	(0.010)	(0.016)
	[0.009]	[0.013]	[0.008]	[0.010]
	{0.006}	{0.008}	{0.006}	{0.009}
	Additional effects on off-road grid cells			
Off-road × Distance from border			-0.156	-0.144
			(0.032)	(0.076)
			[0.026]	[0.061]
			{0.020}	{0.050}
Off-road × Distance from road			-0.009	-0.008
			(0.001)	(0.002)
			[0.001]	[0.001]
			{0.001}	{0.001}
Off-road × Bilateral exports			0.069	0.805
			(0.187)	(1.405)
			[0.140]	[1.162]
			{0.106}	{0.769}
Off-road × Bilateral exports × Distance from border			0.032	0.030
			(0.012)	(0.018)
			[0.009]	[0.012]
			{0.007}	{0.010}
Off-road × Bilateral exports × Distance from road			-0.002	-0.002
			(0.000)	(0.001)
			[0.000]	[0.001]
			{0.000}	{0.001}
Off-road cells	NO	NO	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic		(15)		(13)
		[16]		[15]
		{17}		{17}
# Observations	648,783	648,783	648,783	648,783

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses (1,639 clusters).

Standard errors clustered at road level in brackets (5,250 clusters).

Spatially clustered standard errors in curly brackets (following Colella, Lalive, Sakalli and Thoenig, 2018). We allow for spatial correlation up to 1,000 kilometers, and for serial correlation up to 5 years.

Table A9: First stage results for within-road specification

Dependent variable:	Bilateral exports	Bilateral exports × Distance from border	Bilateral exports × Off-road	Bilateral exports × Off-road × Distance from border	Bilateral exports × Off-road × Distance from road
	(1)	(2)	(3)	(4)	(5)
Distance from border (in 10km)	0.001	5.567***	-0.000	0.144**	0.138**
	(0.001)	(0.605)	(0.000)	(0.062)	(0.059)
Tariffs imposed by neighbor country (in logs +1)	-0.124***	0.471***	0.188**	0.348**	0.200***
	(0.014)	(0.149)	(0.089)	(0.168)	(0.033)
Tariffs imposed by neighbor country × Distance from border	-0.000	-0.140***	-0.005	0.015**	0.005*
	(0.000)	(0.032)	(0.009)	(0.007)	(0.003)
Off-road × Distance from border	-0.000	-0.044	0.001	5.521***	2.368
	(0.001)	(0.917)	(0.001)	(0.689)	(1.882)
Off-road × Distance from road	-0.000*	0.002	-0.000*	0.002	2.108***
	(0.000)	(0.005)	(0.000)	(0.005)	(0.578)
Off-road × Tariffs imposed by neighbor country	0.009	0.010	-0.015	0.481***	3.833***
	(0.019)	(0.216)	(0.014)	(0.156)	(1.467)
Off-road × Tariffs imposed by neighbor country × Distance from border	-0.000	-0.002	-0.000	-0.141***	-0.060
	(0.000)	(0.047)	(0.000)	(0.034)	(0.069)
Off-road × Tariffs imposed by neighbor country × Distance from road	0.000	-0.000	0.000	-0.000	-0.133***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)
Off-road cells	YES	YES	YES	YES	YES
Controls	ALL	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES	YES
F statistic	22	26	16	24	17
Clusters	1,639	1,639	1,639	1,639	1,639
Observations	648,783	648,783	648,783	648,783	648,783

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A10: Baseline estimates - Pre-sample weights of tariffs

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
	Effects on grid cells along road			
Distance from border (in 10km)	0.170***	0.174***	0.171***	0.172***
	(0.030)	(0.065)	(0.028)	(0.069)
Bilateral exports (in logs)	0.058	0.470	0.080	0.516
	(0.146)	(0.532)	(0.155)	(0.544)
Bilateral exports × Distance from border	-0.030***	-0.029*	-0.033***	-0.031
	(0.010)	(0.021)	(0.010)	(0.025)
	Additional effects on off-road grid cells			
Off-road × Distance from border			-0.156***	-0.135
			(0.032)	(0.091)
Off-road × Distance from road			-0.009***	-0.007***
			(0.001)	(0.003)
Off-road × Bilateral exports			0.069	0.777
			(0.187)	(1.519)
Off-road × Bilateral exports × Distance from border			0.032***	0.026
			(0.012)	(0.021)
Off-road × Bilateral exports × Distance from road			-0.002***	-0.002*
			(0.000)	(0.001)
Off-road cells	NO	NO	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic		12		10
# Clusters	778	778	1,522	1,522
# Observations	104,114	104,114	602,712	602,712

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Tariffs are weighted according to their 1994 volumes.

Table A11: Baseline estimates, different fixed effects

Dependent variable: light intensity per 10x10 km grid cell (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
				Effects on grid cells along road				
Distance from border (in 10km)	0.118***	0.127***	0.111***	0.116***	0.054**	0.089**	0.069**	0.118**
	(0.026)	(0.036)	(0.026)	(0.042)	(0.027)	(0.039)	(0.027)	(0.047)
Bilateral exports (in logs)	0.188***	0.383***	0.207***	0.454***	0.093	0.284	0.080	0.337*
	(0.063)	(0.115)	(0.049)	(0.107)	(0.078)	(0.189)	(0.074)	(0.179)
Bilateral exports × Distance from border	-0.016	-0.019	-0.018*	-0.019	-0.019**	-0.031**	-0.019**	-0.030**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.008)	(0.013)	(0.008)	(0.012)
				Additional effects on off-road grid cells				
Off-road × Distance from border			-0.096***	-0.088*			-0.048***	-0.094***
			(0.030)	(0.052)			(0.019)	(0.029)
Off-road × Distance from road			-0.010***	-0.009***			-0.010***	-0.010***
			(0.001)	(0.002)			(0.001)	(0.002)
Off-road × Bilateral exports			-0.049	-0.014			0.049	-0.042
			(0.051)	(0.082)			(0.084)	(0.227)
Off-road × Bilateral exports × Distance from border			0.018*	0.016			0.015*	0.028**
			(0.011)	(0.014)			(0.008)	(0.013)
Off-road × Bilateral exports × Distance from road			-0.002***	-0.003***			-0.002***	-0.002**
			(0.000)	(0.001)			(0.000)	(0.001)
				Control Variables				
Altitude (in 100m)	-0.093***	-0.086***	-0.063***	-0.066***	-0.100***	-0.090***	-0.050***	-0.057***
	(0.008)	(0.010)	(0.005)	(0.007)	(0.007)	(0.009)	(0.008)	(0.011)
Slope	-0.000	-0.001*	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)
Port closer than next land border (dummy)	1.559***	1.547***	1.052***	1.033***	1.757***	1.671***	1.588***	1.588***
	(0.402)	(0.391)	(0.399)	(0.383)	(0.377)	(0.359)	(0.277)	(0.273)
Port dummy × Distance from port	-0.141***	-0.136***	-0.124**	-0.117***	-0.153***	-0.118***	-0.178***	-0.177***
	(0.046)	(0.042)	(0.051)	(0.041)	(0.041)	(0.044)	(0.055)	(0.061)
Airport closer than next land border (dummy)	1.317***	1.306***	0.764***	0.759***	1.177***	1.122***	0.764***	0.761***
	(0.122)	(0.130)	(0.125)	(0.127)	(0.119)	(0.129)	(0.092)	(0.091)
Airport dummy × Distance from airport	-0.116***	-0.112***	-0.049***	-0.047***	-0.064***	-0.039	-0.035***	-0.034***
	(0.033)	(0.037)	(0.014)	(0.015)	(0.030)	(0.032)	(0.011)	(0.012)
Same ethnicity on both sides of border (dummy)	-0.141	-0.099	-0.113	-0.111	-0.060	-0.052	-0.059	-0.049
	(0.121)	(0.119)	(0.091)	(0.183)	(0.129)	(0.114)	(0.114)	(0.139)
Controls	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	NO	NO	NO	NO
Region-Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Neighbor country-Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Kleibergen-Paap F statistic		23		13		16		12
# Clusters	835	835	1,671	1,671	813	813	1,640	1,640
# Observations	113,512	113,512	649,109	649,109	113,292	113,292	648,787	648,787

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A12: Baseline estimates, including 2013

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV	(3) OLS	(4) IV
	Effects on grid cells along road			
Distance from border (in 10km)	0.181***	0.190***	0.185***	0.195***
	(0.028)	(0.054)	(0.022)	(0.060)
Bilateral exports (in logs)	0.070	0.441	0.095	0.502
	(0.130)	(0.430)	(0.109)	(0.427)
Bilateral exports × Distance from border	-0.032***	-0.036***	-0.035***	-0.036**
	(0.010)	(0.014)	(0.011)	(0.016)
	Additional effects on off-road grid cells			
Off-road × Distance from border			-0.160***	-0.152**
			(0.033)	(0.075)
Off-road × Distance from road			-0.009***	-0.009***
			(0.002)	(0.003)
Off-road × Bilateral exports			0.084	0.731
			(0.161)	(1.139)
Off-road × Bilateral exports × Distance from border			0.034***	0.033**
			(0.014)	(0.016)
Off-road × Bilateral exports × Distance from road			-0.002***	-0.002**
			(0.000)	(0.001)
Off-road cells	NO	NO	YES	YES
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic		16		14
# Clusters	1,012	1,012	2,050	2,050
# Observations	150,680	150,680	813,871	813,871

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A13: Overglow, small countries and landlocked countries

Dependent variable: Average light intensity (logs)	(1) IV	(2) IV	(3) IV	(4) IV
Sample	Baseline	Overglow correction	No small countries	Landlocked countries
Distance from border (in 10km)	0.178***	0.174**	0.169***	0.359***
	(0.065)	(0.084)	(0.059)	(0.092)
Bilateral exports (in logs)	0.556	0.538	0.541	0.487
	(0.513)	(0.470)	(0.496)	(0.409)
Bilateral exports × Distance from border	-0.035**	-0.038**	-0.041***	-0.046***
	(0.016)	(0.019)	(0.020)	(0.020)
Controls	ALL	ALL	ALL	ALL
Road FE	YES	YES	YES	YES
Region-Year FE	YES	YES	YES	YES
Neighbor country-Year FE	YES	YES	YES	YES
First-stage F statistic	13	13	12	10
# Clusters	1,639	1,639	1,492	243
# Observations	648,783	648,783	586,661	66,292

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors clustered at road and country-pair-year level in parentheses.

Table A14: Baseline results: grid-cell fixed effects

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effect on grid cells along road		
Bilateral exports (in logs)	0.474***	3.127***
	(0.024)	(0.804)
Bilateral exports × Distance from border	-0.006	-0.215***
	(0.006)	(0.071)
Additional effect on off-road grid cells		
Off-road × Bilateral exports	-0.227***	-3.854***
	(0.014)	(1.018)
Off-road × Bilateral exports × Distance from road	-0.002	0.206***
	(0.004)	(0.084)
Off-road × Bilateral exports × Distance from border	-0.002***	0.027**
	(0.000)	(0.011)
Controls	ALL	ALL
Grid cell FE	YES	YES
First-stage F statistic		3
# Clusters	5,255	5,255
# Obervations	648,572	648,572

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A15: Heterogeneous effects with respect to differences in 1990 GNI

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Distance from border (in 10km)	0.161***	0.169***
	(0.025)	(0.027)
Bilateral exports (in logs)	0.050	0.405
	(0.113)	(0.417)
Bilateral exports × Distance from border	-0.026***	-0.030**
	(0.008)	(0.009)
GNI 1990 (in logs) × Distance from border	0.021***	0.023**
	(0.007)	(0.011)
GNI 1990 × Bilateral exports	0.040***	0.065***
	(0.012)	(0.021)
GNI 1990 × Distance from border × Bilateral exports	-0.006***	-0.004***
	(0.002)	(0.001)
Off-road cells	NO	NO
Controls	ALL	ALLL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		12
# Clusters	812	812
# Observations	113,289	113,289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A16: Heterogeneous effects with respect to differences in 2015 GNI

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Distance from border (in 10km)	0.146***	0.161***
	(0.026)	(0.031)
Bilateral exports (in logs)	0.048	0.392
	(0.094)	(0.364)
Bilateral exports × Distance from border	-0.023***	-0.025**
	(0.005)	(0.006)
GNI 2015 (in logs) × Distance from border	0.024***	0.028***
	(0.007)	(0.009)
GNI 2015 × Bilateral exports	0.042***	0.068***
	(0.014)	(0.022)
GNI 2015 × Distance from border × Bilateral exports	-0.007***	-0.004**
	(0.002)	(0.002)
Off-road cells	NO	NO
Controls	ALL	ALLL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		12
# Clusters	812	812
# Observations	113,289	113,289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A17: Border cities (population cut-off = 100,000)

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effects on rural roads		
Distance from border (in 10km)	0.105***	0.092***
	(0.032)	(0.032)
Bilateral exports (in logs)	0.254	0.343
	(0.177)	(0.240)
Bilateral exports × Distance from border	-0.013***	-0.015***
	(0.004)	(0.005)
Additional effects on urban roads		
Road leading to city >100k (dummy) × Distance from border	0.087***	0.129**
	(0.038)	(0.059)
Road leading to city >100k × Bilateral exports	0.117***	0.176***
	(0.039)	(0.052)
Road leading to city >100k × Distance from border × Bilateral exports	-0.040***	-0.050***
	(0.013)	(0.018)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		12
# Clusters	776	776
# Observations	100,928	100,928

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A18: Cities across the border

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effects on roads without a city across the border		
Distance from border (in 10km)	0.108***	0.091***
	(0.026)	(0.027)
Bilateral exports (in logs)	0.233	0.336
	(0.176)	(0.231)
Bilateral exports × Distance from border	-0.010**	-0.011**
	(0.005)	(0.005)
Additional effects on roads with a city across the border		
Road leading to foreign city >500k (dummy) × Distance from border	0.074**	0.099**
	(0.035)	(0.048)
Road leading to foreign city >500k × Bilateral exports	0.079*	0.121*
	(0.049)	(0.078)
Road leading to foreign city >500k × Distance from border × Bilateral exports	-0.024***	-0.031***
	(0.010)	(0.016)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		15
# Clusters	812	812
# Observations	113,289	113,289

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A19: Cities on either side of the border

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effects on rural roads		
Distance from border (in 10km)	0.117***	0.109***
	(0.032)	(0.033)
Bilateral exports (in logs)	0.212	0.230
	(0.168)	(0.184)
Bilateral exports × Distance from border	-0.009**	-0.014**
	(0.004)	(0.006)
Additional effects on urban roads		
Road leading to city >500k × Distance from border	0.061**	0.072**
	(0.031)	(0.033)
Road leading to city >500k × Bilateral exports	0.120**	0.187**
	(0.052)	(0.085)
Road leading to city >500k × Distance from border × Bilateral exports	-0.028***	-0.039**
	(0.011)	(0.017)
Additional effects on roads with a city across the border		
Road leading to foreign city >500k × Distance from border	0.010	0.028
	(0.009)	(0.030)
Road leading to foreign city >500k × Bilateral exports	0.034	0.067*
	(0.031)	(0.037)
Road leading to foreign city >500k × Distance from border × Bilateral exports	-0.007*	-0.012
	(0.005)	(0.010)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		11
# Clusters	776	776
# Observations	108,019	108,019

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A20: Border cities: industrialized countries

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effects on rural roads		
Distance from border (in 10km)	0.173***	0.187***
	(0.049)	(0.061)
Bilateral exports (in logs)	0.197*	0.282*
	(0.127)	(0.160)
Bilateral exports × Distance from border	-0.016***	-0.022***
	(0.006)	(0.007)
Additional effects on urban roads		
Road leading to city >500k × Distance from border	0.069**	0.085**
	(0.032)	(0.038)
Road leading to city >500k × Bilateral exports	0.314*	0.392*
	(0.171)	(0.223)
Road leading to city >500k × Distance from border × Bilateral exports	-0.030***	-0.041***
	(0.011)	(0.012)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		8
# Clusters	207	207
# Observations	36,635	36,635

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A21: Border cities: developing countries

Dependent variable: Average light intensity (logs)	(1) OLS	(2) IV
Effects on rural roads		
Distance from border (in 10km)	0.113**	0.125**
	(0.054)	(0.061)
Bilateral exports (in logs)	0.186	0.239
	(0.160)	(0.195)
Bilateral exports × Distance from border	-0.011**	-0.015**
	(0.005)	(0.007)
Additional effects on urban roads		
Road leading to city >500k × Distance from border	0.099**	0.108**
	(0.047)	(0.048)
Road leading to city >500k × Bilateral exports	0.370	0.444
	(0.286)	(0.295)
Road leading to city >500k × Distance from border × Bilateral exports	-0.036***	-0.055***
	(0.013)	(0.017)
Off-road cells	NO	NO
Controls	ALL	ALL
Road FE	YES	YES
Region-Year FE	YES	YES
Neighbor country-Year FE	YES	YES
Kleibergen-Paap F statistic		12
# Clusters	591	591
# Observations	71,298	71,298

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two-way clustered standard errors at road and country-pair-year level in parentheses.

Table A22: Summary statistics: main crops

Crop	# cells	Percent
Barley	29,170	3.39
Cassava	64,196	7.45
Cotton	32,487	3.77
Groundnut	1,644	0.19
Maize	179524	20.84
Millet	24,988	2.90
Oilpalm	11,616	1.35
Potato	24,670	2.86
Rice	76,834	8.92
Rye	48	0.01
Sorghum	49,576	5.76
Soybean	63,955	7.43
Sugarcane	7,356	0.85
Sunflower	5,308	0.62
Wheat	289,958	33.66
Total	861,330	100.00