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Free Trade Agreements and Development: a Global Analysis with Local Data

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Abstract

This paper analyzes the effects of Free Trade Agreements (FTAs) on various measures of local development in 207 countries over the 1990-2015 period. Using a Difference-in-Differences approach, I exploit spatial and time variation by comparing regions with (exogenously determined) exploitable and non-exploitable land before and after FTAs are "activated". I show that FTAs have a limited yet positive impact on a region's human development (as measured by the Human Development Index). The results also indicate that this limited impact can be explained by the positive effects of Free Trade Agreements on economic activity (night lights and GDP), together with the lack of significant influence on patterns of inequality (distribution of night lights among population). Finally, I also show that FTAs' impacts on human development are stronger for urbanized regions. Conversely, there is neither clear evidence of a weaker positive effect if trade partners belong to the Global North nor if the agreements include arrangements beyond the elimination of tariffs and quotas.

JEL Codes: F13, F63, R12

Keywords: FTAs, Human Development, Economic Activity, Inequality

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1 Introduction

Trade is one of the most pervasive processes of economic globalization, yet, so is the discontent with agreements liberalizing it. Since the industrial revolution, costs associated with trade have exponentially decreased, inviting even geographically isolated countries to participate. As a result, trade interactions among countries have flourished, along with the incentives to exchange even further. The signing of the General Agreement on Tariffs and Trade (GATT) in 1947 was arguably the role model of block and bilateral trade agreements that later followed in Western countries. Since then, trade agreements have taken many forms, with Free Trade Agreements (FTAs) and preferential trade agreements (PTAs) being the most encompassing examples. Both types have been rather ubiquitous throughout the second part of the 20th century and the beginning of the 21st. The importance of such agreements is not only defined by their ubiquity, but, more importantly, by their capacity to set the rules of the trade game. This game, as most games, results in winners and losers and should be regarded as a risk worth taking. However, what if the winners represent only a stark minority worldwide? Or even worse, what if the winners are systematically favored by the rules of the game?

Classical economic literature predicts that countries will benefit from increased exposure to trade; however, evidence of anti-FTA attitudes is neither scarce nor regionally concentrated. For instance, consider the case of Latin America vis-à-vis more developed regions. On the one hand, the adoption of Free Trade Agreements has remained a recurrent debate throughout Latin America for more than three decades (Falconí and Acosta, 2005; Paz y Miño Cepeda, 2007; Bohigues and Rivas, 2019).[1] Few would consider Latin America as a region winning the trade game in the end, as its countries—e.g., Mexico or Colombia—have often been explored as case studies for the negative consequences of FTAs (Otero, 2011; Salamanca et al., 2009). On the other hand, while the latter might lead to believe that trade agreements are to be contested only in developing regions –as predicted by Heckscher-Ohlin's theory[2]– rallies against them can be traced back to at least the seventies in developed countries as well (Held and McGrew, 2007; Reitan, 2012).[3] Indeed, the widespread mobilizations in Europe against the Transatlantic Trade and Investment Partnership (TTIP) in 2015, and the street demonstrations that have taken place since 2004 in South Korea and China against a trilateral FTA with Japan, are just some examples of an existing anti-FTA attitude in the developed world (Teney et al., 2014). Losing in the FTA game then may very well not be exclusive to

[1]The recurrent meetings of the World Social Forum in the region are one of the most tangible demonstrations of such debates. The World Social Forum is an almost annual event that, since 2001, has gathered social movements that protest various epiphenomena of globalization, especially regarding economic liberalization and their effects on inequality (Seoane and Taddei, 2002).

[2]For an empirical discussion, see O'Rourke (2003).

[3]These demonstrations have also appeared in various, less straightforward, cultural forms (see Blyth, 2002; Camic and Gross, 2004; Tonkiss, 2006; Béland, 2009).

developing regions but rather a globally expected outcome for specific groups within nations (Kriesi et al., 2012; Flesher Fominaya, 2014).

This potentially negative, global outcome, however, has not hindered the proliferation of FTAs worldwide. As a matter of fact, the relative number of more complex forms of FTAs has dramatically increased since 1990 (Dür et al., 2014), and most economists would still argue that free trade is a superior form of economic policy vis-à-vis protectionism.[4] The question of *why* Free Trade Agreements seem to provoke a backlash from heterogeneous labor groups worldwide yet continue to be a common and sometimes praised instrument of globalization remain both unanswered and relevant. In this paper I explore the impact of FTAs on both human and economic development at the subnational level in order to determine whether real world manifestations against FTAs can be associated with particular effects of such free trade policies on overall welfare.[5]

The empirical approach utilized makes use of a global high spatial-resolution land cover data (ESA, 2017) which describes the predominant type of land—e.g., cropland, urban land, bare land, etc.—on the surface of subnational areas between 1992 and 2015, and a time-series (1990-2015) national-level proxy of FTAs' depth for a maximum of 207 countries (Dür et al., 2014). By exploiting subnational and variation over time via a difference-in-differences design, it is possible to overcome the well-known endogeneity of trade policies. Namely, I estimate the local impact of Free Trade Agreements by comparing their effects on subnational regions with naturally-determined exploitable and non-exploitable land cover. The relevant dummies then are specified as $Post_{j,t-\tau}$ (FTAs' dummy) and $Treat_i$ (land cover dummy). Countries that have an FTAs' depth indicator ≥ 1 are coded as $Post_{j,t-\tau} = 1$, and are countries that, some years before the analysis of indicators of development, have signed trade agreements with at least a substantive provision on tariffs and quotas of goods. Regions with exploitable land ($Treat_i = 1$) are areas covered mostly by cropland, urban areas, natural vegetation, or consolidated bare land, whereas non-exploitable regions ($Treat_i = 0$) are areas covered predominantly by non-consolidated bare land (e.g., deserts), water bodies, or permanent snow and ice.[6] My identifying assumption is that other than via the impact of Free Trade Agreements, and conditional on the use of relevant covariates such as country-year and regional fixed effects, development trends in subnational regions with and without naturally(exogenously)-determined land cover should not be different. Indeed, I test the common pre-trends assumption and find no evidence of a threat on this regard.[7] In other words, I rely on

[4]See Fourcade (2009), Rodrik (2018).

[5]Giuliano and Spilimbergo (2014) show that economic shocks can alter policy preferences and, therefore, in adverse economic environments one can expect people to blame recently introduced economic policy such as FTAs.

[6]In Section 2 I go into more detail about the construction of the referred $Post_{j,t-\tau}$ and $Treat_i$ dummies.

[7]If pre-trends represented a threat for identification, development across regions with and without exploitable land cover would have to show different trends before the FTAs' activation period, yet no

an identification strategy that uses a conditionally exogenous interaction (treatment). Thus, the interaction of interest between $Post_{j,t-\tau}$ and $Treat_i$ is not correlated with the error term and, therefore, is indeed conditionally exogenous to the development outcomes analyzed.

To account for a more holistic understanding of development, I run tests on local proxies of human development, economic activity, and inequality: Human Development Index, night lights, GDP, and inequality—constructed by this author based on the distribution of night lights among the population.[8] The main results show that, in regions with exploitable land (treated regions), vis-à-vis non-exploitable regions (control regions), the local effect of FTAs on human development is *positive* (sig. at the 5% level) and leads to an average change of 0.00046 points (0.0029 standard deviations) on the Human Development Index.[9] I argue that this small, yet positive impact on human development is best explained by an increase of economic activity that does not alter inequality levels; in other words, the benefits brought by a general increase of trade and economic activity do not effectively translate into welfare as levels of inequality are not significantly impacted. This mechanism was tested in various ways. To begin with, I show that FTAs have a *positive* impact on economic activity, measured by an increase of night light emissions and GDP, and *no* impact on the night lights' GINI index. The estimated increase of night lights and GDP is of 9.7% and 6.8% (both at a 1% level), respectively.

I also constructed country groups based on different measures of inequality, and show that, while the effects of FTAs on human development are rather *negative* for *more unequal* countries, their *positive* effects on economic activity remain mostly undifferentiated from the ones seen in more equal nations. In other words, while the increase in economic activity is statistically similar across country groups, the negative impact on human development is stronger for more unequal countries. Even when, in some cases, the positive effects on GDP and night light are statistically different between more or less equal countries, the effects are always larger in more unequal nations. Depending on the country grouping used, the decreases of the human development index in more unequal countries range between 0.04 and 0.14 percentage points, while the increases in night lights and GDP range between 6.4% and 18.3%.

FTAs, nevertheless, are agreements involving provisions that differ from dyad to dyad, from agreement to agreement, and from sector to sector. Therefore, I look into complementary answers in the form of impact heterogeneity. First, I separate FTAs

evidence of such trends was found.

[8] The Human Development Index is an indicator that assesses key dimensions of human development, such as health, education and income, with figures between 0 and 1, where 1 refers to the highest degree of development, and 0 to the lowest.

[9] For context, the average inter-annual change of HDI at the country level between 1990 and 2015 was 0.0051 UNDP (2017). The average 5 year change was 0.026. The effect found then would represent approximately 9.2% of the historical yearly change average, and 1.8% of the 5-year historic change.

signed with countries of the Global North from those signed with the Global South. In principle, given that my main indicator of FTAs conveys standardized information on the FTAs' depth, their effects should be indistinguishable as the FTAs' depth indicator does not discriminate between partner types to determine the FTAs' depth figure—it only focuses on the legal provisions included in such an agreement. However, authors like Diwan and Rodrik (1991), Marchetti and Mavroidis (2011), and Sell (2011) have argued that developed countries' gains have come at the expense of developing countries for some types of trade agreements—e.g., the protection and enforcement of intellectual property rights found in the Trade-Related Aspects of Intellectual Property Rights (TRIPS) mostly benefited pharmaceutical companies located in the Global North, and made medicine nearly unaffordable for people from countries of the Global South.[10] While the estimated effect of FTAs signed with countries of the north is of a smaller size, it is not statistically different from the impact generated by FTAs signed with countries of the south. Second, drawing from Rodrik (2018), I look into the role of added complexity (or depth) to FTAs. This added complexity comes in the form of added legal provisions that go beyond the usual elimination of tariffs and quotas. Other works (e.g., Sakyi et al., 2017) have shown that an increase of legal complexity can increase transactional costs and therefore hinder potential benefits of any other policies. Although the effect of more complex FTAs is negative, I do not encounter robust evidence signalling that such effect is significantly different from that of simpler or less deep FTAs. Third, I look into heterogeneities across economic sectors. Different levels of skills associated with each sector and region can inform the effect of trade (Van den Berg, 2012; Hausmann and Hidalgo, 2010; Hidalgo, 2015; Balland et al., 2020). My estimates reveal that urban-associated productive regions perform better than any other exploitable region. These results are in line with regional studies that show structural differences in diverse human development measures in favor of urbanized areas.

Previous works assessing the effects of trade policy on development explore mechanisms such as power relations, cultural values, human capital accumulation, or the efficiency of institutions (see among others, Ferguson, 2006; Acemoglu and Robinson, 2012; Gokmen, 2017; Jensen et al., 2017). While these conduct tests beyond simple correlations, trade policies are fundamentally politically-informed arrangements whose causes and effects are difficult to identify. My model exploits an exogenous interaction that overcomes the analytical problem of endogeneity in such works.

Attempts around the identification of trade effects at the national level already exist, however (among many others, Frankel and Romer, 1999; Were, 2015). On the one hand, Frankel and Romer's country-level work tried to circumvent endogeneity by creating

[10] This argument also connects with the rationale of the uneven geographic distribution of wealth covered in the core-periphery literature (a.o. Hirst, 1997; Wallerstein, 1976, 2005), where a geographic division of globalization winners (countries of the Global North) and losers (countries of the Global North) is also drawn.

a geographic instrument to assess the effect of trade on income. On the other hand, Were's piece concentrates on the differential impacts of trade on growth in what he categorizes as developed, developing, and least developed countries. While both works find positive effects of trade on indicators of economic growth, their results show either low significance levels of the main effects, or country-specific heterogeneities. Moreover, other specific national-level impact assessments of FTAs' role on economic development are either anecdotal (Francois et al., 2005; Athukorala and Kohpaiboon, 2011; Busse and Groening, 2011) or very specific to particular elements of trade, such as trade flows or technology adoption (Bustos, 2011; Beyene, 2014; Parra et al., 2016). Closest to my work's mechanism discussion is the contribution by Artuc et al. (2019) and Cingano (2014). They argue that while income growth seems to be consistent for countries that have liberalized trade, increases in inequality are also. Inequality, as explained before, is the main mechanism explored in my work to reconcile the considerable impact of FTAs on a region's economic activity and its limited positive role on the same region's human development. Altogether, the results of the studies mentioned suggest that within-nation mechanisms are yet to be understood. The gap is even more evident for local-level studies and, to the best of the author's knowledge, this is the first global work assessing the impact of FTAs on subnational development.

Furthermore, FTAs are arrangements regarding trade, not human development per se. Good-quality, local-level trade data with panel dimension is unavailable for the majority of the world. Thus, one cannot directly assess the impact of FTAs on trade. There are, however, local economic indicators that might proxy trade and economic activity in general well enough. Two of those indicators are GDP and night lights. The use of such indicators, together with a measure of inequality (night lights GINI), represents another contribution of this work to the literature given that the joint assessment of levels of economic activity and inequality can provide an overview of the economic development of the studied region. As economic progress is one of the key bridges between low- and high-levels of human development, to understand FTAs' impacts on human development one needs to have a clear grasp of their effects on more direct forms of such development, i.e., on economic development. Indeed, my work assesses not only the impact of FTAs on indicators of human development but also on indicators of economic improvement (GDP, night lights, and night lights GINI).

To address robustness, I conducted several more tests. For instance, inspired by Christian and Barrett (2017), I show that both exploitable and non-exploitable regions share parallel trends in their human development indicators before the FTA's activation period. Similarly, given that the effective implementation of FTAs may differ greatly from country to country (Stevens et al., 2015), I also look into the role of FTAs-effect time structure. As the main analysis explores the mid-term effects of FTAs and therefore uses a lag of five years, I test other time specifications and control for different activation periods to assess whether they have a significant role on the impact of FTAs. The main estimated effect is consistent for most time-structures tested—even when all activation periods are used in tandem—suggesting that the small yet positive impact of FTAs is robust in the mid-term. Furthermore, I also explore time-placebo tests, i.e., leads of the preferred activation period. As expected, the placebo variables' coefficients are not statistically significant and barely affect the efficiency of my main estimator. Similarly, one of the concerns regarding my preferred specification arises from the absence of controls, besides the set of fixed effects, and the possibility that the absence of further covariates produces an omitted variable bias. It is partly shown that this concern is inconsequential in the main result tables, where I demonstrate that the inclusion of my preferred covariates does not affect the efficiency of the main point estimates. An additional test includes other geographic, political economy, and population controls and shows they are also of little relevance. Another common concern relates to the composition of the reference group and, specifically, to the lack of non-exploitable regions in some countries. As explained before, non-exploitable regions are areas that are mostly covered by non-consolidated bare land, permanent ice, or water. While few in number, there are countries that do not have such regions and therefore only have areas with consolidated bare land, urban areas, cropland, natural vegetation, or a mixture of these on their surfaces. For that reason, I run my main model including only a subsample of countries that have at least one non-exploitable region within their national borders. The results indicate that neither the inclusion of more covariates nor the exclusion of countries without non-exploitable regions bias the main results and, therefore, that the main results explored are robust to a potential omitted variable bias.

This work sheds light on the effects of FTAs on different indicators associated with development. It reconciles the impact of FTAs on human development by assessing the interaction between changes in economic activity and inequality patterns generated by the same FTAs. Moreover, it uses information on most countries of the globe and, thus, is more generalizable than previous studies using a limited number of countries (and usually using different empirical strategies, which limits comparability). An additional advantage of global yet highly disaggregated data is the possibility to explore local heterogeneities and unveil subnational causal mechanisms. Local identification is key because studies with lower spatial resolution can hide dynamics or impact heterogeneities mostly visible at the subnational level, e.g., power capture and its subsequent inefficient redistribution. Moreover, national-level studies lack by construction the statistical power of local-level studies, which pragmatically facilitates the analysis for researchers. For policy makers, this work offers key lessons about the conformation and negotiation of FTAs by shedding light on the aspects of an agreement that they should closely inspect, e.g., the sectoral composition of their economies. However, more importantly, it provides lessons about the goal indicators to be stressed in trade agreements since accounting for impacts on inequality is shown to be key to translating increased levels of economic activity into increased levels of human development.

This work is divided into five sections. In Section 2, I discuss my identification strategy and I detail my data. In Section 3, I explore the main results and, subsequently, some of the potential alternative answers to the main causal mechanism explored (Section 4). In the final section, I summarize my work and state the human and economic development, as well as the sectoral, legal, and geographic implications of the results for future research and trade policy-making.

2 Identification Strategy

Country-level studies mostly refer to the elimination or reduction of tariffs and quotas as one of the main transmission mechanisms between a trade-related shock and economic development, as FTAs should positively impact development through less restricted trade.[11] The meta-analysis by Stevens et al. (2015), for example, suggests that less than 5% of the literature shows a negative effect of FTAs on volumes of trade. However, while tariff alleviation can bring higher margins of utility to both demand and supply via costs reductions of raw, intermediate, and final products (Amiti and Konings, 2007), this mitigation could also compromise countries' long-term welfare via loss of competitiveness in international markets and recurrent trade deficits (Astorga, 2010; Furceri et al., 2018). There are also other strands of the trade literature that consider that some FTAs have paved the way for the protection of particular commercial interests. In other words, through increased networking—with influential political spheres—transnational companies strengthen their market influence both across and within nations. This literature argues that such dynamics then contribute to an already unequal redistribution of wealth between countries of the Global North and Global South (Diwan and Rodrik, 1991; Caliendo et al., 2015).

Most of these works nevertheless use incompatible identification strategies (i.e., different models, country sample, units of observation, etc.), limiting comparability, and in turn, making any generalizable, conclusive statement on FTAs' impact on trade, let alone development, at least questionable. Moreover, the studies use national-level data that conceal subnational transmission mechanisms and effect heterogeneities, which local data can address more plausibly. Still, local analyses are not always straightforward as

[11] Classical trade theory argues that free trade is a superior form of commercial policy. The theory argues that even when trade liberalization produce losing parties, compensatory measures could potentially support such parties (Hicks, 1939; Kaldor, 1939). The possibility to enact such counter-measures then should converge towards a Pareto optimality. This dynamic, however, might make sense if FTAs were shaped in a highly simplified setting, abstracted from political and cultural, thus neglecting the potential systematic role of power relations, institutional or regulatory flaws, cultural counter-values, etc. on redistribution patterns. Therefore, such pareto interpretation fades away in the current (complex, diverse, mobile) context of globalization.

subnational data are often not comparable across countries due to their uneven quality. Fortunately, with the increasing accessibility to remote-sensing data, such studies have become more attainable. Perhaps the most relevant example using local data—and closely associated to this study—is the work by Henderson et al. (2018). Their work argues that economic development (proxied by night light satellite imagery) derives from the interplay of determinants such as trade intensity, geographical traits (e.g., distance to partner, altitude, temperature, relative distance to coast, etc.), and a path-determined human capital that divides the globe between early- and late-developed countries.[12] These types of studies, however, which analyze the local level impact of FTAs in heterogeneous countries, are still scarce. Given the limited empirical evidence using local level data, and the lack of replicability of national studies on the matter, it is safe to argue that the economic impact of FTAs on development is not yet fully understood. To the best of the author's knowledge, no work has yet assessed FTAs' impact on development using local-level data.

This study focuses on the impact of FTAs on local development. To identify such impact, I implement a particular form of a difference-in-differences (DID) model that uses different activation periods, i.e., an event study. The intuition behind my strategy is the same as that in a difference-in-differences design, where one investigates the effect of a shock by comparing a treated and a control group over time. I exploit the interaction of local land cover traits to distinguish between treatment and control groups (i.e. cross-sectional variation) and the FTA status of a country to divide between pre- and post-periods of the treatment (i.e. time variation). In other words, I look into the effect of Free Trade Agreements in subnational regions with contrasting land exploitability. Naturally, endogeneity concerns arise mainly regarding the adoption of FTAs given that it normally depends on the partner countries' pre-agreement strengths and weaknesses, and therefore, they are hardly exogenous to a region's development. To address part of the potential endogeneity (omitted variable bias), I control for their direct effects on economic development using country-year fixed effects. The set of country-year fixed effects captures the direct impact of trade agreements given that FTAs are determined, precisely, at the country-year level. In my main model I also use regional fixed effects, as I am also interested in directly controlling for subnational determinants of the development (land cover being one of those determinants). Thus, FTAs' and land cover's direct effects cannot be correlated with the error term and, therefore, the interaction between my dummies of land cover and FTAs conforms as a plausible, conditionally exogenous impact for my measures of development. The exogeneity of this interaction however, is strengthened further as the predominant land cover on the regions under study is naturally-determined,

[12] In early-developed countries, as Henderson et al. (2018) argue, high human capital and high trade (transportation) costs informed an even (geographically) settlement of productive activities. In late-developed countries, low human capital and the same trade costs (path-) determined the high geographic concentration of production.

and therefore, is a priori exogenous; had it not, diverging pre-trends of development across regions with and without exploitable land would have to exist before FTAs' "activation". Following Christian and Barrett (2017), I plot the variation (Figure 1) in regions with different types of land cover together with the variation in human development for the period before the activation of Free Trade Agreements. As can be seen, the graph provides little reason to believe that the parallel-trends-before-treatment assumption is violated while trends in human development seem rather parallel across those regions with predominant non-exploitable land and those with mostly exploitable land from $t-10$ until $t = 0$. Moreover, in Table 8 I explore the association between figures of development and future FTAs' impacts in both non- and exploitable regions and find no correlation between them. My identifying assumption then is that controlling for country-year and region fixed effects, and other potentially relevant covariates, development outcomes in subnational regions with naturally-determined exploitable and non-exploitable land, will not be affected differently in the post-period, other than via the impact of the trade agreements.

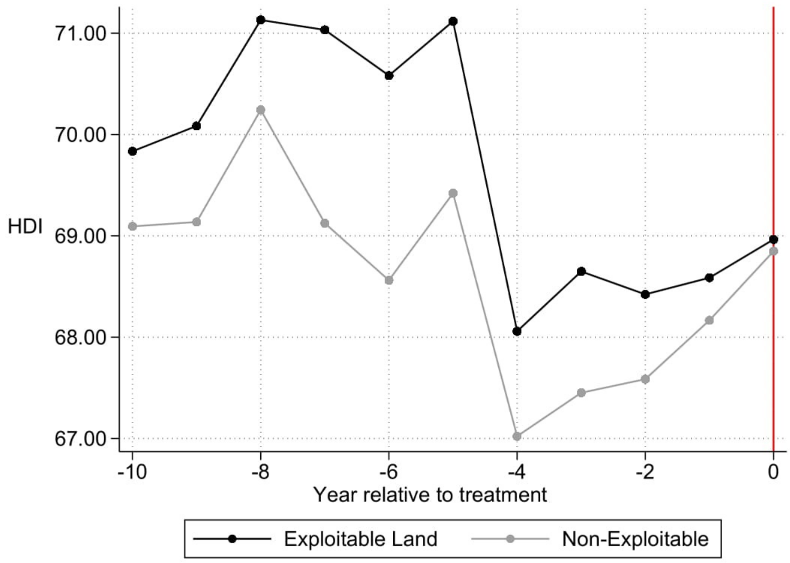


Figure 1 – Testing for Spurious Trends

Notes: The figure shows the average HDI levels for regions with exploitable land (black line), and without exploitable land (gray line), 10 years before FTAs' activation period (red vertical line). HDI is scaled ($\times 100$).

The implementation of my DID was carried out as is commonly done in these setups, and therefore initially constructs two main dummies: *Post* and *Treat*. The usual *Post* dummy then takes the value of 1 when t corresponds to the post-treatment period, and 0 when it corresponds to a pre-treatment period—note that, given that my DID uses different activation periods, the units of analysis might have different pre- and post-treatment periods. In parallel, the dummy *Treat* takes the value of 1 for a unit in the treated group (exploitable-land region), and 0 for a unit in the control group (non-exploitable-land region). The interaction of these two dummies then constitute the interaction of interest, $Post \times Treat$. Thus, my initial specification has the following general form:

$$Development_{i,t} = \beta_1 Post_{j,t-\tau} \times Treat_i + \beta_2 Z_{i,t-1+}\beta_3 \eta_{j,t} + \beta_4 \gamma_i + \epsilon_{i,t} \tag{1}$$

$Development_{i,t}$ is the average level of development in region i in year t. The components of the $Post_{j,t-\tau} \times Treat_i$ interaction follow the observational rules described in Table 1. Z is a vector of several individual (region) political economy and geographic controls, which I describe below. η_{jt} and γ_i represent the country-year and region fixed effects, respectively. Note that both the dummies $Treat_i$ and $Post_{j,t-\tau}$ are not separately included in equation (1) as these are directly captured by the region γ_i and country-year fixed effects $\eta_{j,t}$, respectively. In other words, I later show that the predominant land cover of region i is time-invariant, and thus, that this characteristic is effectively captured by the region fixed effects included in equation (1). Similarly, the FTAs indicator of any region i is defined at the national level, and while does vary over time, the country-year fixed effects capture the impacts of these FTAs, yearly changes. Recognizing the likely spatial- and time-correlation across my error terms, the standard errors ϵ are clustered at the regional and country-year level.

Table 1 – Observational Rules

Country j,t **Post = 1**		**Region i** **Treat = 1**	**All**	**Agriculture**	**Manu&Serv**	**Other**	**Reference Group**
FTA depth $\geq$ 1 in t-τ	&	Exploitable land (10 $\leq$ Mode LC $\leq$ 190 and Mode LC = 201) in i	1	0	0	0	0
FTA depth $\geq$ 1 in t-τ	&	Cropland (13 $\leq$ Mode LC $\leq$ 30 and Mode LC = 10) in i	0	1	0	0	0
FTA depth $\geq$ 1 in t-τ	&	Urban land (Mode LC = 190) in i	0	0	1	0	0
FTA depth $\geq$ 1 in t-τ	&	Other expl. land (30 < Mode LC < 190 and Mode LC = 11-12)	0	0	0	1	0
FTA depth $\geq$ 1 in t-τ	&	Mostly non-exploitable land (190 < Mode LC < 220 exc. 201) in i	0	0	0	0	1

Note: As seen, the range of land for our most general treated group, namely *Treat*=1, would be for Mode land cover figures between 10-190 or equal to 201, and the reference group would range between 190 and 220 – with the exception to a Mode LC value of 201. The Mode LC values are at the regional level. FTA depth is the average depth level of all FTAs signed per country-year, and its depth is determined as detailed in Table 2. The lag on FTA depth is $t - \tau$, where my preferred specifications use a τ of 5.

Table 1 delves into the main dummies of interest. Namely, the first row of the table details the observational rules of the local regions under study for equation (1). I code the treatment period or $Post = 1$ if the region-year observation belongs to the period post-FTA's treatment. Consider region i; if the average FTA in the region includes provisions on—at least—tariffs and quotas (i.e., FTA depth[13] $\geq$ 1) in t-τ, then for all years after t, $Post_{j,t-\tau}$ will be set to 1. It follows that for all periods before t, the $Post_{j,t-\tau}$ dummy is set to 0.[14] I test several time structures, yet my preferred specification uses a

[13]In Table 2, I explain the construction of this variable in detail.

[14]In Table A.5 of the Appendix A, I run tests using a "generalized" difference-in-differences approach. The approach allows for the $Post_{j,t-\tau}$ dummy to "activate" on the exact period when FTAs treat the regions under study (i.e., $Post_{j,t-\tau} = 1$), and "deactivate" on the periods when there is no FTAs treatment (i.e., $Post_{j,t-\tau} = 0$). The results are qualitatively comparable to those of the main tables.

$\tau = 5$ given that I am mostly interested in the impact of FTAs in the mid- to long-term. Furthermore, I define as exploitable regions ($Treat_i = 1$) those areas where there is, predominantly, cropland, urban land, other forms of natural vegetation, or consolidated bare land—those which have a mode land cover between 10 and 190, or equal to 201. The control group of non-exploitable regions, or $Treat_i = 0$, are defined as those regions with mostly unconsolidated bare land, water, or permanent snow and ice covering them—i.e., a mode land cover greater than 190 and smaller than 220, with exception to those with mode LC equal to 201.[15] As $Post_{j,t-\tau}$ varies over time at the national level, and $Treat_i$ incorporates information that changes at the regional level, their interaction—as in any standard DID—effectively exploits time and space variation.

I illustrate the regional, land cover division in Figure 2 by using the example of the state of Utah in the United States. In my sample, 3 out of 25 subnational regions in the north-east of Utah are defined as "non-exploitable". Those regions are mostly covered by water or bare unconsolidated land and, therefore, according to my characterization, these are areas where it is considerably more difficult for productive activities or factories to settle or thrive.[16] It follows that the rest (22 out of 25) of the subnational regions in Utah are "exploitable". Contrary to the "non-exploitable" regions, these areas are mostly covered by shrubland and trees, which I argue makes them more suitable for new ventures to come in and grow.

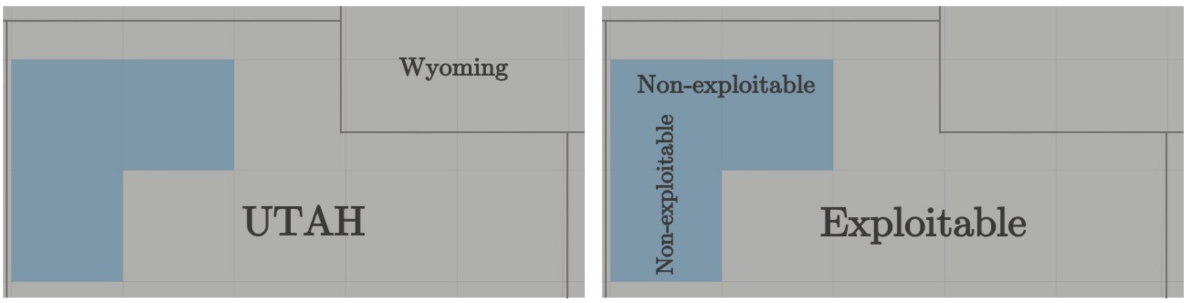


Figure 2 – Subnational regions of Northern Utah

In this way, I pose that the non-exploitable regions constitute a relevant control group for the effect of FTAs at local levels given that they simulate the non-treated status of countries that have not experienced an economic shock, including an FTA shock. For instance, countries might only be indirectly—if at all—affected by trade shocks in their neighboring countries via spillovers (see Khan, 2020). At the subnational level, one may indeed see such mechanics both at the borders of the neighboring "non-exploitable" regions and in the exploitable regions surrounding them (as in Figure 3).

[15]Figure 4 presents the main land cover categories exploited in this work.
[16]Given that fishing industries can indeed settle in areas mostly covered by water, in Table A.2 of Appendix A I run robustness tests where I code regions mostly covered by water bodies as "exploitable". The results are qualitatively identical.

While exploitable regions seem to grow uniformly across space and exponentially over time, the non-exploitable areas seem to marginally grow at the borders when neighboring exploitable regions. Indeed, between 1992 and 2013, the red-marked exploitable regions experienced a 146.25% increase of its mean night light output, whereas the non-exploitable region experienced just a 9.06% increase. This is the kind of dynamic that I expect post economic shock from exploitable and non-exploitable regions, ceteris paribus.

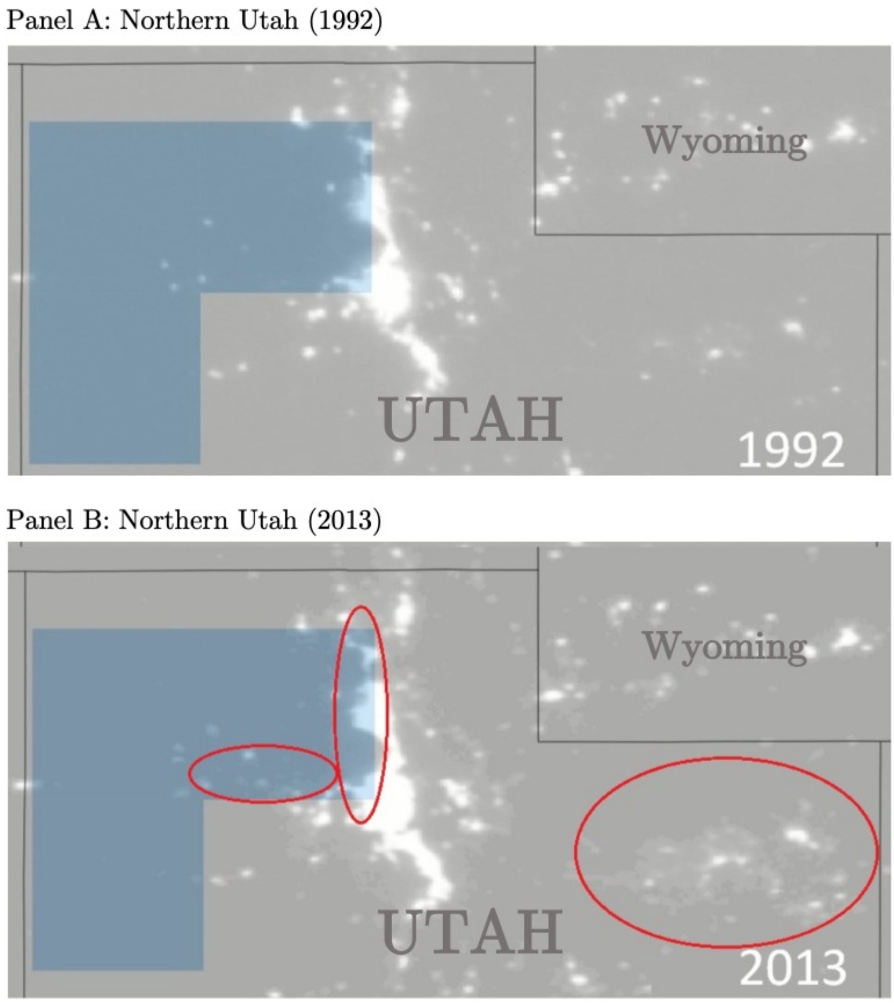


Figure 3 – Growth and spillovers of night light on exploitable and non-exploitable regions.

Notes: Areas marked by red show a significant increase of night light output between 1992 and 2013.

2.1 Data

Studies assessing development at the subnational level are increasingly common. The works by Sutton and Costanza (2002) or Sutton et al. (2007) canonized the use of remote sensing data by using night light emissions to proxy levels of economic activity at the local level. Night-time light emissions (night lights) are one of the most standardized proxies for economic activity. Apart from its panel and global nature, which adds to comparability, it reduces the recurrent measurement error in the production of local data, which is common in developing regions of the world. Henderson et al. (2012) and Jean et al. (2016) furthered the use of remote sensing data in development studies by proposing the prediction of rates of growth and poverty via the use of geographically-detailed data, e.g., altitude, temperature, geo-location. Upon these works, the literature has expanded with new ways of assessing satellite imagery's quality (Chen and Nordhaus, 2011; Chen, 2016; Mellander et al., 2015) and associating it to development. Night lights, for instance, have not only been shown to be correlated to economic activity but also to figures of wealth, health, or education (Noor et al., 2008; Weidmann and Schutte, 2017; Bruederle and Hodler, 2018).

I use a baseline sample of countries that have engaged in FTAs in the last three decades and construct subnational geographic divisions within those countries to study the local impact of FTAs. In total, the study encompasses 19,033 unique region cells—each roughly 111 by 111 km in size—that cover 2078 provinces/states and 207 countries of the world, during the 1990-2015 period. This paper assesses the impact of FTAs on local human development by using the subnational Human Development Index (HDI) (Kummu et al., 2018). The HDI portrays the degree of overall accomplishment in fundamental development dimensions considered by the human development definition of the United Nations: health, education, and economic development (UNDP, 2017). These dimensions are measured by jointly assessing the life expectancy at birth, the expected years of schooling, and the gross national income per capita of the regions under study. The subnational index includes global data between 1990 and 2015, which have a (roughly) 10 km-at-the-equator spatial resolution, and that were generated using different country- and local-level datasets. For non-European countries and based on a nearly complete, global subnational HDI report of 2009, Kummu et al. (2018) mostly used country-specific censuses and UNDP reports to extrapolate the equivalent HDI figures for subnational regions in years where information was not available. For European countries, Kummu et al. (2018) used the subnational HDI data of the Eurostat directly and extrapolated data points using national-level data on population and HDI when the data were not available. Similarly, in order to better understand the causal mechanism of FTAs on HDI, this paper studies the effects of FTAs on local economic development and uses various indicators: night lights, GDP, and subnational inequality.

The night light data come from satellite imagery generated by the Earth Observation Group, part of the National Oceanic and Atmospheric Administration of the United States NOAA 2015. The dataset covers the 1992-2013 period and has a spatial resolution of 1 by 1 km. For GDP, I also use the datasets constructed by Kummu et al. (2018).[17]

[17]Both night lights and GDP figures are skewed to the right; therefore, in order to smooth them out, I use the log of their values in all preferred specifications. I also use the inverse hyperbolic sine function for my preferred specifications, as seen in Table A.1 in the Appendix A. For completeness, tests on their raw values were conducted resulting in qualitatively comparable outcomes. The details of such computations

Their work contains values on subnational GDP from 1990 until 2015 at a roughly 10 by 10 km resolution, expressed in constant 2011 US dollars. The data on GDP are key to understanding the effects of FTAs on economic activity too, while, apart from adding robustness to potential results on night lights, it is a good proxy for local trade.[18] The subnational inequality indicator was constructed following Elvidge et al. (2012). This inequality measure uses the Lorenz curve principle to plot the cumulative distribution of night lights against the cumulative distribution of population density. For each year, I first sort grids of 55 km^2 (h) from the lowest to the brightest average night light intensity jointly with the respective population count within my units of analysis—grids of 111 km^2 (i). Lorenz curves are then generated and used to compute inequality (night lights GINI) for all 111 km^2 subnational regions. In other words, the coefficient is computed as the area between the Lorenz curve and the diagonal (0.5), divided by the area above the diagonal (0.5), as in[19]:

$$Inequality_{i,t} = \frac{0.5 - \int_0^1 (CumulativeLight_{h,i,t} vs. CumulativePopulation_{h,i,t})}{0.5} \qquad (2)$$

This results in an index that resembles the income Gini index, ranging from 0 to 1, where 0 represents the highest level of inequality and 1 the lowest.[20] The local population data that I use come from the History Database of the Global Environment (HYDE) produced by Goldewijk et al. (2011), and has a spatial resolution of roughly 10 km^2.

The main goal of this paper is the measurement of the effect of national- or supra national-level arrangements at the local level. This is the case of FTAs as their figures are aggregated at the country level—with the exception of supranational regions like the EU. To overcome this shortcoming I combine the local data on human and economic development with an interaction of indicators of (national) FTAs and (local) land cover, and argue that the interaction delivers a good proxy for the subnational shock of such national FTAs variables. Following this logic I create dummies for each subnational region to capture information on FTAs' presence and land exploitability as a productive region—as explained in detail in the above, and particularly on Table 1 and Figure 2.

are available upon request.

[18]FTAs have previously been shown to be robustly and positively associated with trade in several studies (Stevens et al., 2015). Similarly, trade and GDP are positively correlated at national levels, as can be seen in Table A.15 in Appendix A.

[19]A graphical representation of such a computation by Elvidge et al. (2012) can be seen in Figure C.1 in the Appendix.

[20]One can worry that such a local inequality measure is driven by the variation of night lights or population data. This concern was indeed shared by the author and was the main reason why smaller regions ($< 55km\hat{}2$) within the areas studied (111 km^2) were not constructed. Doing so would have increased the probability of distortions driven especially by the population data. However, to test whether the inequality measure is driven by the light or population data, in Table A.16 I run a correlation test between the indicators of night lights and population with the one on inequality. As seen, such correlation is pretty low, which suggests that neither night lights or population is driving such inequality measure.

The data on FTAs come from the work of Dür et al. (2014), who construct country-level indicators for the depth or conditions added to 1,002 FTAs since 1948. The FTAs' depth is an additive indicator of the type of provisions that a particular FTA includes that ranges between zero and seven, i.e., higher values of FTAs' depth include all conditions/provisions corresponding to lower FTAs' depth values—as detailed in Table 2.[21] For instance, the values of *depth* ≥ 1 refer to FTAs with almost no tariffs and quotas for most goods, whereas the values *depth* ≥ 2 refer to agreements that, apart from eliminating barriers on tariffs and quotas, include the elimination of most impediments on the exchange of services. My sample consists of 749 different FTAs negotiated between 1990 and 2015, and I construct the main indicator of FTAs' depth as an annual average of FTAs signed by a country in a year.

Table 2 – FTA depth (additive index)

Legal Provision	**Value**
1. More than a partial scope agreement (on goods)	$FTA\ depth = 1$
2. Substantive provision on services and 1.	$FTA\ depth = 2$
3. Substantive provision on investments and 1.to 2.	$FTA\ depth = 3$
4. Substantive provision on standards and 1.to 3.	$FTA\ depth = 4$
5. Substantive provision on public procurement and 1. to 4.	$FTA\ depth = 5$
6. Substantive provision on competition and 1. to 5.	$FTA\ depth = 6$
7. Substantive provision on intellectual property rights and 1. to 6.	$FTA\ depth = 7$
Total range	0-7

Note: Table based on Dür et al. (2014, pp.34)

The remote-sensing land cover data describe the surface of the land, i.e., whether it has cropland, shrubland, water bodies, bare spaces, etc. The data do not describe the suitability of the land but rather the actual characteristics of the land covering the region's surface. These land cover (LC) records come from the work of the European Space Agency (ESA) and the Climate Change Institute, which released the LC project in 2017 (ESA, 2017). The LC data are global, include yearly information from 1992 to 2015, and use the Land Cover Classification System (LCCS)[22] designed by the Food and Agriculture Organisation (FAO) to categorize different types of land cover. The spatial resolution of the data is mostly at 300m—with some areas up to 30 m. In order to define the predominant category of LC in region i of 111 km^2, I use the mode of LC categories within region i. Thus, as shown in Figure 4, if the mode LC value of region i is for instance urban land, I define urban land as the predominant LC in region i, or similarly, if the mode LC value of region i is agricultural land, I then define agricultural land as the predominant LC in region i. One might be concerned that the LC mode is not the

[21] I consider "accessions" as different FTAs while they add a new country to the deal and as my analysis is at the subnational region-year level.

[22] The LCCS data legend is included in the Appendix, Table B.3.

right proxy to establish the predominant type of land in any region i. However, note that the spatial resolution of the land cover data—30 to 300 meters—is high enough to argue that, in a region of 111 km^2, the LC mode approximates the region's most common land cover category. Note that, depending on the resolution of land cover data in region i—as said, 30 or 300 meters—each area of 111 km^2 would consist of 137,174 or 1,371,739 land cover data points or pixels.[23]

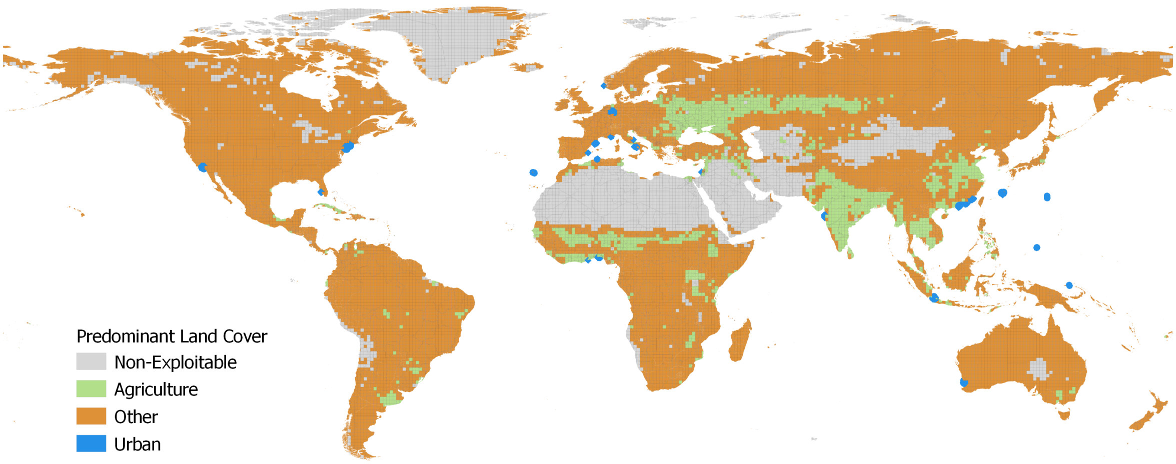


Figure 4 – Subnational Land Cover categories

I turn now to the description of the control variables that I use in the main tables to further reduce potentially omitted variable concerns. Being under a particular FTA is arguably correlated with factors that affect development differently in regions with high or low exploitability. For instance, the degree of exploitability could be correlated with geographic patterns (e.g., temperature, distance to cities), which could imply that any differential effects of land cover on development resulted from those patterns rather than from the contrasting endowments of exploitable land. The data on temperature is computed by using the PRIO-GRID vector grid Tollefsen et al. (2012). It is yearly calculated as the mean degrees Celsius within the region i. Apart from controlling for temperature, I include a distance-covariate utilized in the geography-trade literature analysis: distance to capital city (Allen and Arkolakis, 2014; Martin and Pham, 2020; Rauch, 2016). The distance variable comes also from the PRIO-GRID dataset, and is computed as the average distance (in km) from region i to the capital city. I also use two political-economy controls, namely the birth region information of leaders of the executive (Hodler and Raschky, 2014) and aid disbursements by the World Bank (AidData, 2017). The birth region variable is meant to capture the role of political favoritism on a region's development. Hodler and Raschky (2014) show that leaders seem to favor their birth regions as suggested by higher night light emissions and aid amounts in areas close to

[23]For robustness, I also used the mean LC value per region to define economic sectors. Results do not change qualitatively and are available upon request.

their birthplaces. I construct a dummy indicating whether the leader of a country j is in office by year t_{-1} and was born in region i. Following Hodler and Raschky's rationale, I expect significant results on development a year after the leader took office. I thus include the lagged dummy variable in the covariates vector. The data were directly provided by Hodler and Raschky. Similarly, Dreher et al. (2019) show that one of the channels of favoritism is aid. Moreover, Cruzatti C. et al. (2020) show a relevant impact of aid on health indicators. In this study I use the geo-referenced data constructed by AidData.org on World Bank (WB) from 1995-2015, and calculate the region's yearly mean WB aid disbursements in constant 2014 USD. I only use projects that have coordinates with exact location information, within 25 km, or refer to the center of the country's second order administrative division—depending on the country, either province or state.[24]

2.2 Remaining Identification Concerns

My estimation strategy combines the use of national- and local-level data. Due to the precision of the local data, one might circumvent problems of omitted variable bias of national data or lack of statistical power. For instance, exploiting data at finer levels of spatial resolution allows for the inclusion of finer levels of fixed effects, thus controlling for potentially unobserved determinants of the effect more precisely.

On the one hand, in the context of national-level models of trade, one of the axioms is that international exchange is directly proportional to the size of the country and inversely proportional to the distance of the counterpart (the so called "gravity model", e.g., Rauch (2016)). These models argue that the geographic distance between industries is a relevant explanatory variable of varying levels of trade. One can claim that this study does not include such a control on distances between compatible sectors (i.e., with the same predominant land cover) and therefore might ignore a problematic correlation of my interaction of interest with the error term that contains the unexplained determinants of development. The distance between regions with the same predominant sector (land cover), however, varies across regions but not over time and, thus, their potential correlation is already captured by the regional fixed effects in the model. On a similar note, one may also be concerned about the human- or technology-associated malleability of land cover at the regional level, which would threaten an—arguable—as-if randomness and time invariability of the predominant types of land covering my studied regions and, ultimately, the identification of the local effects of FTAs. Indeed, due to human intervention, predominant land cover in a region could change and its direct effects then would not be captured by the chosen level of fixed effects. However, while theoretically possible, the probability to do so, such that the predominant LC of areas of 111 km by

[24]Tables B.1 and B.2 in Appendix B show the study variables' sources and definitions, and their descriptive statistics, respectively.

111 km changes in a few years, is small. For instance, the share of regions in my sample that experience at least one change from a land category to another in any of the years under study is only 4.10% (780 out of 19,033). Among this 4.10%, 99.23% of them (774 out of 780) return shortly thereafter to their most frequent category and, therefore, were easily categorized as either exploitable or non-exploitable regions. These facts strengthen the assumption of time-invariant land cover for any region i, which in turn render the set of fixed effects of my specifications sufficient. Nevertheless, robustness tests with specifications dropping units that experience land-category changes were conducted in Table A.3 of Appendix A.[25]

On the other hand, there may remain concerns regarding the construction of my $Post_{j,t-\tau}$ dummy. As detailed above, $Post_{j,t-\tau}$ is mainly determined by the FTAs' status. This status is in turn determined by the yearly average "depth" of all trade agreements in a country. Thus, there may be trade-intensity issues that I cannot account for directly. For instance, by taking the average of all FTAs, I assume all partner countries have the same relevance. While numerically speaking this might hold true—i.e., one sovereign country does not count less than any other before the international community because of its size or power—the reality is that some partners are more impactful than others.[26] Therefore, one should control for the size or economic power of the country's partner in order not to bias the FTAs' indicator. Note, however, that such control already exists in my equation (1). The characteristics of trade partners of any country for any year t are already captured by the inclusion of country-year FE, as they control in its most general form for all year-to-year determinants of economic development in the countries under analysis.[27] In other words, country-year FE capture national-year-specific characteristics that could have an impact on the development of all regions in a particular country, with one of these characteristics being the size or power of its trade partners. Notwithstanding all the latter, I run several robustness tests detailed in Appendix A where I explore different constructions of the FTA variable instead of the dichotomous $Post_{j,t-\tau}$ presented in equation (1). Namely, in Table A.6 I use the number of FTAs signed in any given year (($FTANumber_{it-5}$), in Table A.7 I use the mean depth of FTAs signed in any given year ($FTADepth_{it-5}$), and finally, in Table A.8 I differentiate between big and small countries and interact such categorization with my main $Post_{j,t-\tau}$ variable. Results do not challenge my main findings and are detailed in the Appendix section.

[25]No qualitative change in the main results were found.

[26]Imagine the case where a small country like Ecuador signs an FTA with Paraguay, with a depth equal to 1 in year t. Now lets imagine that in $t+1$ Ecuador signs another FTA, with the same depth of 1, but with the USA. For computation purposes, Ecuador will have the same FTA figure in year t and $t+1$ even when the partner's power, economically and politically, is incomparable.

[27]Even supranational characteristics—such as belonging to blocs like the European Union, for example—since the country-year fixed effects are already absorbing more precise territorial variation.

3 Results

Table 3 shows the results for the impact of FTAs on the Human Development Index of the subnational regions studied. All columns reflect the effect of FTAs on a scaled HDI (HDI×100). Columns 1 to 6 report the estimates for equation (1) and include fixed effects progressively. In columns 1 to 3 I report the results without the geographic and political-economy controls described in Section 2. In columns 4 to 6 I include the controls detailed in the previous section. My preferred specifications correspond to those in columns 3 and 6, which include the full set of fixed effects at the country-year and regional (individual) level. In all the result tables, the discrepancy between the number of observations in the specifications that include all control variables and those that do not stem from the missing values in the dataset of the temperature variable.

Table 3 – FTAs and Human Development

	(1) **HDI**	(2) **HDI**	(3) **HDI**	(4) **HDI**	(5) **HDI**	(6) **HDI**
$Treat_i \times Post_{jt-5}$	2.249**	0.223	0.046**	-4.487**	0.945***	0.098**
	(1.134)	(0.243)	(0.023)	(1.739)	(0.348)	(0.039)
$Treat_i$	2.049**	0.435***		7.338***	-0.066	
	(0.895)	(0.167)		(1.553)	(0.277)	
$Post_{jt-5}$	-0.356			2.350*		
	(1.261)			(1.245)		
Observations	450,237	449,786	449,786	238,673	238,453	238,453
Adjusted R-squared	0.009	0.949	0.997	0.260	0.946	0.997
Controls	NO	NO	NO	YES	YES	YES
Country-Year FE	NO	YES	YES	NO	YES	YES
Region FE	NO	NO	YES	NO	NO	YES
Countries	207	190	190	193	175	175
Regions	18392	18375	18375	16737	16719	16719

Notes: All HDI values are scaled (HDI×100). When specified, columns include country-year and regional fixed effects. When specified, the set of controls includes temperature, World Bank aid, Leaders' birth regions and mean distance to capital city (when region fixed effects are not used). Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

In order to get a first insight into the potential impact of FTAs on human development, columns 1 and 4 describe the impact of FTAs on the Human Development Index without fixed effects. Columns 1 and 4 report a statistically significant figure for my coefficient of interest, β_1. The results, however, show contradictory patterns; while column 1 shows an increase of 2.249 percentage points (p.p.) on the HDI at the 5% level, column 4 shows a detrimental effect of 4.487 p.p. Although the inclusion of covariates in column 4 means the sample is not directly comparable to the one used column 1, if the results were to be robust to different types of bias, one would expect qualitative similar patterns to be observable in the variables of interest. Given that FTAs are negotiated at the country level—and sometimes even at higher levels, such as the European Union—it makes sense that non-captured country heterogeneity is able to distort results in such a way. In columns 2 and 5 I turn to a specification that includes the use of country-year fixed effects. Columns 2 and 5 report a positive effect of FTAs on HDI. While column 2 shows an increase of 0.223 percentage points (p.p.) on the Human Development Index, column 5 shows a positive effect of 0.945 p.p. The results for column 2, however, are not statistically significant, whereas the results for column 5 are so at the 1% level. Given that there are several non-observed persistent determinants of Human Development at the local level that are also correlated with my variable of interest, such as geographical, cultural, or historical features, it is necessary that one controls for such potential sources of omitted variable bias.

In columns 3 and 6 I turn to the most stringent variations of my model. The results on these specifications show a rather small yet statistically significant positive effect of FTAs on local Human Development. The generated effect ranges between an average increment of 0.046 p.p. (0.29% standard deviations of HDI) in column 3 and 0.098 p.p. (0.56% standard deviations) in column 6. Both coefficients are statistically significant at the 5% level. For instance, consider a subnational region i in period t with an average HDI value correspondent to the sample's HDI mean, 0.71. Based on the estimates shown in column 3, it is expected that five years after the FTA was signed, the HDI value in region i increases to 0.71046. Altogether, the results suggest that the impact of FTAs on human development is small yet positive. The small size of such a positive effect (less than 0.29% standard deviations) of FTAs on Human Development can be potentially explained by an increase of economic activity that does not redistribute opportunities amongst the population. The benefits brought by an increase of trade and economic activity in general might not be effectively translated into human welfare as levels of inequality are not being impacted by such trade agreements. The literature on that regard is vast, yet the trade-growth literature specifically argues that globalization, while having brought about clear progress in areas such as trade and technology, has neglected other necessary elements for development, such as the reduction of inequality (Artuc et al., 2019). The lack of inequality reduction then may play a fundamental role in the low impact of processes of globalization, such as the implementation of FTAs, on the improvement of more comprehensive indicators of development, which by definition transcend the assessment of mere economic activity.

In Table 4, I test potential transmission mechanisms that can explain the limited

Table 4 – FTAs and Economic Development

	(1) **Light**	(2) **Light**	(3) **GDP**	(4) **GDP**	(5) **Inequality**	(6) **Inequality**
$Treat_i \times Post_{jt-5}$	0.097***	0.081***	0.068***	0.041	0.0001	0.011
	(0.021)	(0.027)	(0.018)	(0.032)	(0.006)	(0.009)
Observations	389,968	209,911	448,021	237,763	358,031	197,855
Adjusted R-squared	0.972	0.980	0.985	0.984	0.706	0.693
Controls	NO	YES	NO	YES	NO	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Countries	200	176	193	176	185	173
Regions	18046	16392	18400	16722	17169	16111

Notes: Light and GDP are logged. All columns include country-year and regional fixed effects. When specified, the set of controls includes temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

positive impact of FTAs on human development.[28] On the one hand, I assess FTAs' role in economic activity, measured as changes in yearly average night light emissions (columns 1 and 2) and GDP (columns 3 and 4). To the extent that FTAs directly impact levels of trade (Stevens et al., 2015), one should see this impact translated into changes in measures of economic activity that straighforwardly capture increasing/decreasing levels of trade, such as GDP.[29] However, the impact of FTAs on economic activity can also be indirectly seen in the form of infrastructure needed for the establishment of production lines and, therefore, that one should see an increase of night light emissions in places where economic activity has thrived. [30] In principle, the effects on night lights and GDP should be qualitatively similar given the elsewhere shown correlation between the two; however, one can argue that potential discrepancies can be explained by the straightforwardness of the impact of one (night lights) in comparison to the more layered impact of the other (GDP). While night lights directly describe the state of infrastructure and thus indirectly describe the level of aggregated economic activity, GDP is a direct measure of such activity informed by several—sometimes hard to quantify—productive activities that do not necessarily rely on night light infrastructure in order to materialize.

[28]The number of total observations vary across dependent variables given that periods and local availability of data differ for each variable. In Table A.9 for the first four columns, I run tests restricting the sample to the time period available for all dependent variables: 1992-2013. In the last four columns of the table, I also restrict the sample to the minimum number of non-missing data for all specifications. Results remain qualitatively unchanged.

[29]As GDP = C + I + G + (X − M), where C is consumption, I is investment, G is government spending, X is exports, and M is imports.

[30]Indeed, many authors have already shown such an association between economic activity and night lights (Sutton and Costanza, 2002; Sutton et al., 2007; Weidmann and Schutte, 2017).

I also evaluate the effect of FTAs on local inequality (columns 5 and 6). Varying levels of inequality have been shown as being key to explaining varying levels of development (Cingano, 2014; Artuc et al., 2019). In these works, it is suggested that an increment of economic activity without an improvement of distributive patterns, on average, should distinctively affect places with high and low figures for inequality. That is, an increment of the economic activity in regions with low inequality should be beneficial on average for the region as such activity premiums would be distributed among more portions of the population, making their current development status better off vis-à-vis their ex-ante (pre-FTAS) status. Conversely, an increment of economic activity in areas with high inequality should have no significant (or even negative) effects for the region's human development on average, as such premiums would concentrate in fewer hands and, hence, widen the access gap to basic goods and services—the access to which constitute a pillar of human development—between upper- and lower-income households.

Similar to Table 3, the uneven columns of Table 4 report the results with the full set of fixed effects but without other controls. The even columns show the results with the inclusion of the full set of fixed effects and further controls. As can be seen, the results between the two specifications are highly comparable for all outcomes. Columns 1 and 2 report the positive and statistically significant (at 1% level) impact of FTAs on logged night light. The coefficients of interest are nearly equal, i.e., FTAs provoke a 9.7% increase of the geometric mean of night lights for column 1 and 9.5% in column 2. This means that, if the night light output of any region i was 10 in period t, one would expect to see that this region's night light increases to approximately 11 in $t + 5$. Similarly, columns 3 and 4 report the positive impact of FTAs on logged GDP. The coefficients of interest are quantitatively comparable, i.e., FTAs leading to a 6.8% increase of the geometric mean of GDP in column 3 and a 4.6% increase in column 4—the latter coefficient, however, is not statistically significant. For instance, for a region i with a GDP output of 1,000,000 USD in year t, the GDP figure will have grown to 1,068,000 five years after FTAs were introduced. The results on GDP and night lights indicate that FTAs do bring an expansion of economic activity in the areas where they are introduced. I conclude this table by assessing the impact of FTAs on inequality in columns 5 and 6. The coefficients of the interaction are quantitatively similar; the effect of FTAs on inequality is rather small and positive but not statistically significant.[31]

[31] As Salvati et al. (2017) argue, a limitation of the indicator of night light inequality is that it can take similar values for areas that have contrasting degrees of luminosity. This is specially relevant in areas with a low number of people living in them. That is, a region with its entire population living in almost complete darkness will have the same (perfect) inequality value of 0 as regions where all their population have access to the same level of brightness—as what the indicator measures is the (un-)equal distribution of night lights. For this reason, I run robustness tests separating grids with a number of people above and below the median—many more (population-wise) splits were attempted, yet, results were always qualitatively similar, therefore, are not included in this study (they can however be requested directly from the author). I also winsorize the indicator of night lights inequality to values closer to the minimum and maximum values of income Gini coefficients in the study period: 0.20-0.66. This way, I

Taken together, the results of Table 3 and Table 4 suggest that the lack of impact by FTAs on inequality diminishes the overall benefits on human development that FTAs otherwise do bring to economic activity. This is in line with the hypothesis that the reduction of inequality is a key factor to the improvement of human development. In parallel, the results of Table 3 and Table 4 also show that the inclusion of geographic and political economy controls do not qualitatively change the coefficients of interest. Thus, to avoid the loss of too many observations due to missing values for the control variables—temperature being the most relevant, with 242,919 missing values— and if not specified otherwise, the remaining specifications of the main text will compute the model of equation (1) without such controls. In Table 9 I nevertheless run a robustness test to assess whether such controls could represent a threat or not to the identification of my main effect. The results are displayed in Section 4.

In Table 5 I explore the mechanism by means of which inequality can affect economic and human development. If inequality is indeed the catalyzing factor between economic activity and human development, high inequality patterns should aggravate the results shown in Table 3, i.e., I expect more unequal regions to show poorer human development figures while maintaining positive and comparable levels of economic activity. In other words, I expect that poor effects on human development figures, such as those shown in Table 3, are more noticeable (even smaller or negative) for more unequal regions, and that the overall performance of economic activity (measured in changes of GDP and night lights) remains positive and comparable between regions of contrasting levels of inequality.

can restrict computations to historically more representative figures of inequality. Results are shown in Table A.10 and portray how, only when the range of night light inequality is brought to the historic maximum and minimum Gini values (column 4), an increase of inequality becomes significant at the 10% level. These results strengthen the argument that FTAs do not significantly improve inequality, and if anything, worsen it.

Table 5 – Mechanism: Inequality

	Local Inequality		Historic Inequality		Year-to-year Inequality		LAC vs. The World		Henderson's Early-Late		Henderson's Early-Late: Adjusted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	HDI	**Light**	**HDI**	**Light**	**HDI**	**Light**	**HDI**	**Light**	**HDI**	**Light**	**HDI**	**Light**
$Treat_i \times Post_{jt-5}$	0.117***	0.069**	0.113***	0.091***	0.100***	0.002	0.052**	0.097***	0.076***	0.054*	0.124***	0.033
	(0.035)	(0.030)	(0.030)	(0.033)	(0.028)	(0.035)	(0.024)	(0.022)	(0.023)	(0.030)	(0.023)	(0.032)
$Treat_i \times Post_{jt-5} \times AvgIneq3y_{it}$	-0.092***	-0.023										
	(0.025)	(0.020)										
$Treat_i \times Post_{jt-5} \times Unequal_j$			-0.140***	0.008								
			(0.044)	(0.043)								
$Treat_i \times Post_{jt-5} \times Unequal_{jt}$					-0.051*	0.089**						
					(0.029)	(0.045)						
$Treat_i \times Post_{jt-5} \times LAC_j$							-0.123**	-0.007				
							(0.052)	(0.062)				
$Treat_i \times Post_{jt-5} \times LateDev_j$									-0.043	0.183***	-0.125***	0.179***
									(0.055)	(0.044)	(0.047)	(0.042)
Observations	280,724	277,213	409,862	360,304	194,340	174,713	449,786	389,968	304,221	267,287	304,221	267,287
Adjusted R-squared	0.997	0.976	0.997	0.973	0.997	0.973	0.997	0.972	0.997	0.976	0.997	0.976
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Countries	184	185	156	158	141	140	190	200	116	116	116	116
Regions	17157	17167	16717	16655	16329	16118	18375	18046	12346	12342	12346	12342

Notes: All HDI values are scaled (HDI×100). All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

I test such a dynamic in Table 5, by separating subnational regions and countries of the globe in different ways. First, in columns 1 and 2 I use the local measures of inequality of Table 3 and 4 to construct a three-year average of subnational inequality and assess its continuous role on the impact of FTAs at the local level.[32] Second, in columns 3 and 4 I separate countries between those below and above the historic world median of income inequality ($Unequal_j$), measured by the income GINI index. Third, in columns 5 and 6 I divide nations between those below and above a time-variant world median of inequality using the same GINI index. Fourth, in columns 7 and 8 I separate Latin America from the rest of the world as countries of this region have been commonly associated with higher levels of income inequality, as seen for 2016—year with more complete data in the study period—in Figure C.2 in the Appendix. Finally, in the last four columns (9-12) I divide the sample following the distinction used by Henderson et al. (2018) between early- and late-developers, as in Figure 5.

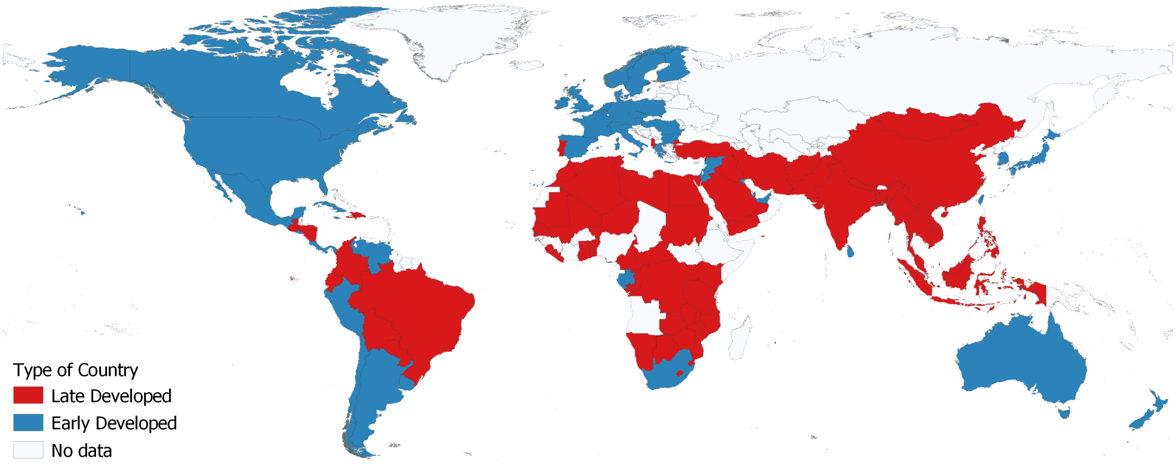


Figure 5 – Stages of Development by 1950

Notes: Late developed countries do not trespass any of the development cut-offs proposed by Henderson et al. (2018). Early developed countries surpass at least one of the three indicators.

Henderson and co-authors implemented this categorization by considering the average performance of countries in 1950 for three elements: education, GDPpc, and urbanization. If a country in their sample passes their established performance threshold in any of the three elements, a country is categorized as early-developed. Conversely, countries that do not pass any of the thresholds are categorized as late-developed countries. Given that access to such development-related elements are key to understanding the main sources influencing the gap between upper and lower socioeconomic classes, the Henderson et al.'s distinction constitutes a straightforward proxy for a Global North-South division that focuses on the analysis of the interconnection between inequality, economic activity, and human development.

[32]In Table A.4, I construct different versions of the local inequality measure and use them in tests that use the same specifications of column 1 and 2 of Table 5. Results are qualitatively similar.

Columns 1 and 2 of Table 5 display the impact of FTAs in subnational regions with differing levels of inequality. The columns show that, as inequality increases, the overall positive impact of LAC on the HDI is reduced. Namely, while FTAs effect for totally egalitarian regions is of 11.7%, at the 1% significance level, every percentage point growth of inequality would diminish FTAs' positive impact on the HDI in about 0.0009% percentage points, at the 1% level. Similarly, the table shows that, when statistically significant, the impact of FTAs on the HDI of more equal countries ranges between 0.052 (column 7) and 0.124 (column 11) percentage points. This positive impact however, has a different nature for more unequal countries. Thus, as seen in columns 3, 5, 7, 9 and 11 such impact is greatly undermined. For columns 3, 7 and 11 the total impact of FTAs on human development is even negative among unequal countries. Results portray a different picture on the impact of FTAs on economic activity (night lights), as more unequal regions often benefit more or similarly to less unequal regions. For instance, column 2 shows that the overall positive effect of FTAs on night lights is not different in regions with greater inequality. The positive impact is of 6.9%, at the 5% level, for both unequal and equal regions. Furthermore, when there is a statistically significant difference between regions, such difference goes in favor of the more unequal ones—the marginal increase ranges between 8.9% (column 6) and 18.3% (column 10).[33] The results, however, do pose an intriguing outcome in column 9. This result on HDI shows that, even when the coefficient trends in the same direction of comparable columns, there is no significant difference between the positive impact of FTAs on HDI in regions of countries of the Global North versus that experienced in regions of the Global South. The difference (between column 9 and previous country-divisions columns) can be explained, however, by the precision of the country distinctions made. For instance, while the divisions between countries in terms of *Historic Inequality* (columns 3 and 4) used an objective and more time-relevant period for my sample (GINI indicators from 1960 to 2019), the division that Henderson et al. make, using indicators from 1950, might no longer represent an accurate measure of inequality.[34] For that reason, in columns 11 and 12 I modify the distinction used by Henderson et al. (2018) between early- and late-developers by including as late-developers those countries that rank above the historic median of inequality.[35] As seen, once the adjustment has been introduced, results are coherent with the other figures of the table.

In sum, the interpretation of the results for Table 5 appears to be twofold: 1) both the least and most unequal regions experience economic growth due to the introduction of

[33] I also run tests on GDP instead of Light and HDI in Table A.11 of Appendix A. Results do not qualitatively change the conclusions drawn from Table 5.

[34] For instance, El Salvador is considered by Henderson et al. (2018) as *early developed*, yet its figures of inequality have been larger than the yearly median during most of the years considered in this study —1990, 1995-1996, and 1998-2015.

[35] Only 7 out of 116 countries changed denomination: Costa Rica, El Salvador, Gabon, Jamaica, Mauritius, Panama, and Sri Lanka.

FTAs, yet, and perhaps more importantly, 2) while the least unequal regions experience a general improvement in their human development after FTA's entry, the regions of the most unequal nations experience deterioration in such human welfare indicators. The results suggest then, that inequality is indeed an explanatory factor for the lack of correspondence between the limited benefits brought by FTAs to human development (Table 3) and the considerable effects on economic growth (Table 4).

4 Alternative answers and robustness tests

There are, of course, alternative explanations as to why FTAs impact human development in such a small yet, positive way. In Table 6, I delve into the exploration of some of these potential answers. Diwan and Rodrik (1991) argued that usual legal standards of trade agreements, especially the ones regarding intellectual property rights and patents negotiated in the Uruguay Round, systematically benefit countries of the Global North at the expense of nations of the Global South.[36] Moreover, testing this claim is especially relevant while countries like the United States or supra-regions such as the European Union heavily protect key sectors (e.g., agriculture) in the "free" trade arrangements they enter into (Wise, 2009, 2014; Otero, 2011, Grochowska and Ambroziak, 2018; Grennes, 2018; Kareem et al., 2018). I examine this argument in column 1 and compare FTAs signed with countries of the Global North ($PostNorth_{it-5}$) versus those signed with partners in the Global South ($PostSouth_{it-5}$).[37] If nations of the Global North have systematically captured the benefits of FTAs, differences in the impacts they provoke should be apparent. As can be seen in column 1, the coefficients of interest for $PostSouth_{it-5}$ and $PostNorth_{it-5}$ are positive, yet the effect seems to be weaker for FTAs signed with countries of the Global North. However, the two coefficients are not statistically different from zero, which suggests that the capturing of such benefits is not explained by a differentiation of north and south partners.[38]

Dür et al. (2014) argue that FTAs have become increasingly complex in the last 30 years, including an increasing number of provisions that exceed the usual provisions on tariffs and quotas of past (classic) FTAs, as one can indeed see in Figure 6.[39] Some of

[36] Regarding such patent and IPP regulations included in FTAs, World Health Organisation Director General Dr. Margaret Chan declared about the Trans-Pacific-Partnership in 2015: "...If these agreements open trade yet close the door to affordable medicines, I have to ask the question: is this really progress at all?..." (Germanos, 2015). Also see Marchetti and Mavroidis (2011) and Sell (2011) for further insight on the consequences of the Uruguay Round for developing countries.

[37] More details on the construction of these variables can be found in Table B.1 in the Appendix B.

[38] I also run a test with such division and for the main results of this study in Table A.13 in the Appendix.

[39] According to Limão (2016), by 2011, 76 percent of existing preferential trade agreements were subject to at least one aspect of investment standardization, 61 percent included intellectual property rights protection, and 46 percent demanded environmental regulations.

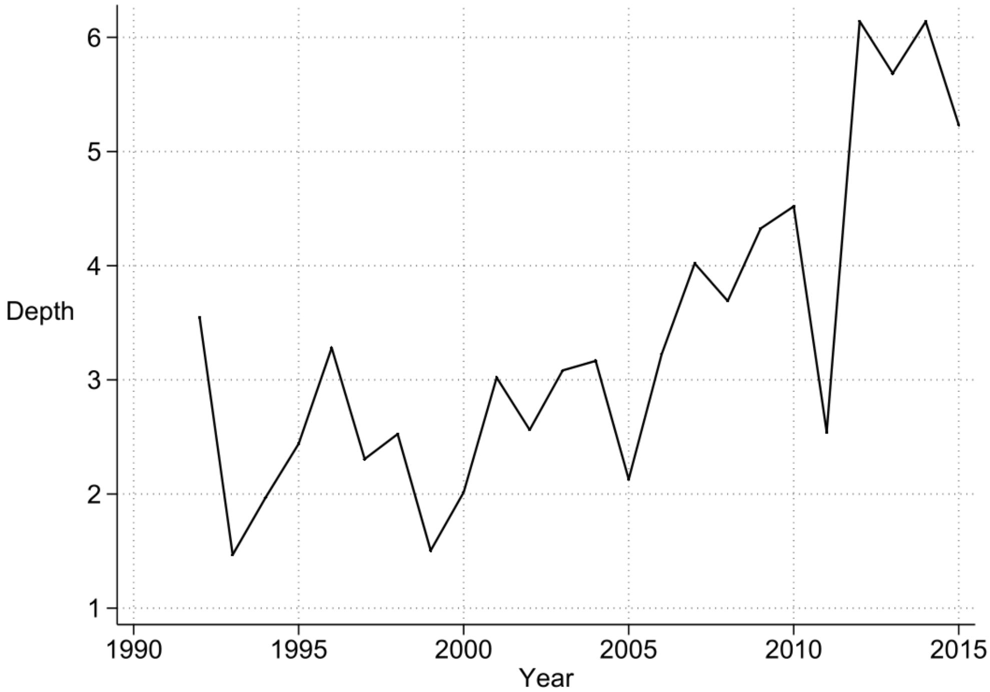


Figure 6 – FTAs depth evolution

these additional conditions concentrate on the establishment of shared regulation and law enforcement in sensitive areas such as product standards and intellectual property rights, but it can also contain binding criteria in areas such as services exchange, investments, and rules of competition. Thus, as Rodrik also argued in 2018, a potential explanation for the impact of FTAs on human development might reside in the (depth) type of FTA that a country signs. In other words, the efficiency of an FTA might be defined by the degree of conditionality that is stipulated in such agreements. In column 2, I define a dummy ($ComplexFTA$) that separates FTAs that, on average, include provisions on tariffs and quotas (FTAs' depth=1) from those which include more than such classic conditions (FTAs' depth$\geq$2). The results show a positive effect of FTAs that only include provisions on tariffs and quotas, and a rather negative effect for FTAs that go beyond. Similarly, in column 3, I run an extension test in which, instead of using a dummy that separates classic FTAs from more complex ones, utilizes the total number of $ComplexFTA$ signed.[40] The direction of the coefficients in this latter column are opposite to those of column 2, yet both the effects in columns 2 and 3 are not statistically significant and therefore do not constitute sufficient evidence for the hypothesis that FTAs' increasing conditionality plays a diminishing role in the FTAs' small yet positive impact on human development.

I conclude Table 6 by exploring another of the most straightforward hypotheses about FTAs' effects on development: sectoral heterogeneities. Otero (2011) and Wise (2009, 2014) argue how the signing of an FTA can compromise the food sovereignty of

[40]More details on the construction of these variables can be found in Table B.1 in the Appendix B.

Table 6 – FTAs impact heterogeneity on HDI

	(1) **FTAs North-South**	(2) **FTAs Conditionality**	(3) **Conditionality: Number FTAs**	(4) **Sectoral Heterogeneity**
$Treat_i \times PostSouth_{it-5}$	0.056			
	(0.035)			
$Treat_i \times PostNorth_{it-5}$	0.010			
	(0.022)			
$Treat_i \times Post_{jt-5}$		0.058	-0.0001	0.047**
		(0.064)	(0.0003)	(0.023)
$Treat_i \times Post_{jt-5} \times ComplexFTA_{it-5}$		-0.014	0.0003	
		(0.064)	(0.001)	
$Treat_i \times Post_{jt-5} \times Agriculture_i$				-0.021
				(0.045)
$Treat_i \times Post_{jt-5} \times ManuServ_i$				0.331**
				(0.148)
Observations	449,786	449,786	449,786	449,786
Adjusted R-squared	0.997	0.997	0.997	0.997
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	190	190	190	190
Regions	18375	18375	18375	18375

Notes: All HDI values are scaled (HDI×100). All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

a country by exposing its agricultural industry to free trade.[41] Similarly, Van den Berg (2012), Hausmann and Hidalgo (2010), and Hidalgo (2015) show how free trade can be particularly beneficial for high-skilled regions that specialize in the provision of services, and that are mostly located in highly-developed cities. Column 4 then poses a sectoral distinction between regions that concentrate on agricultural production $Agriculture_i$ (or that have cropland as the predominant land cover), manufacturing and services $ManuServ_i$ (or that have urban land predominantly), or other regions $Other_i$ that can host productive activities (or that predominantly have natural vegetation or consolidated bare land).[42] In principle this approach would allow for the identification of whether a sector is driving the main results presented in Table 3 or not. The results, however, show that, in line with the general results of columns 3 and 6 in Table 3, all zone types or sectors experience positive effects on HDI due to the presence of FTAs. Note that the negative coefficient on the row detailing the agricultural sector (column 5) is not statistically different from the base interaction ($Treat_i \times Post_{t-5}$) that captures FTAs' impact in

[41] Both Wise and Otero use the case of Mexico and the FTA signed with the United States and Canada in 1994—the North American Free Trade Agreement (NAFTA). They show how NAFTA "devastated" the wheat and grain production in Mexico.

[42] As preliminary validation tests, several thresholds of land cover were randomly defined to categorize regions as agricultural, as services and manufacturing, or as other productive activity. Results increasingly change as the cutoffs between land categories become more random.

other zones. The positive impact seems to be considerably larger for the manufacturing and services sector as the estimate reports an increase of 0.378 percentage points of human development in regions specialized in such sectors vis-à-vis a 0.047 percentage points increase in the agricultural and other sectors.

Table 7 – FTAs' impact on Human Development: time structure

	T=0	**T=1**	**T=2**	**T=3**	**T=4**	**T=6**	**T=7**	**T=8**	**T=9**	**T=10**	**t-1 - t-10**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	t-T										
$Treat_i \times Post_{jt-5}$	0.053**	0.037	0.070***	0.075***	0.087***	0.104***	0.027	0.065**	0.077**	0.083***	0.119***
	(0.022)	(0.023)	(0.023)	(0.019)	(0.025)	(0.023)	(0.026)	(0.026)	(0.031)	(0.023)	(0.032)
Observations	449,786	449,786	449,786	449,786	449,786	449,786	449,786	449,786	449,786	449,786	449,786
Adjusted R-squared	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Countries	190	190	190	190	190	190	190	190	190	190	190
Regions	18375	18375	18375	18375	18375	18375	18375	18375	18375	18375	18375

Notes: All HDI values are scaled (HDI×100). All columns include World Bank aid, leaders' birth regions, country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

I next test the time structure of FTAs' impact on human development. While my main analysis uses a $\tau = 5$ for the construction of my $Post_{t-T}$ dummy, a larger or smaller τ is also plausible. FTAs' effective implementation differs greatly from country to country (Stevens et al., 2015) and from FTA to FTA (Diwan and Rodrik, 1991; Rodrik, 2018), and thus, while in some contexts a short/long lag of its impact is conceivable, in others the use of such lag might not be as persuasive. From columns 1 to 11 of Table 7, I control for different periods ($Treat_i \times Post_{i,t\text{-}T}$) to assess whether they have a significant role on my impact of interest. As can be seen, the significance of my main variable $Treat_i \times Post_{it\text{-}5}$ is not threatened, not even when all activation periods are used in tandem (column 11). The latter results suggest that the small yet positive impact of FTAs is indeed robust in the mid-run ($\tau = 5$).[43]

Table 8 – Time Robustness Tests

	(1) **HDI**	(2) **HDI**	(3) **HDI**	(4) **HDI**
$Treat_i \times Post_{jt-5}$	0.053**	0.054**	0.056**	0.058**
	(0.022)	(0.022)	(0.024)	(0.024)
$Treat_i \times Post_{jt}$		-0.011		-0.020
		(0.035)		(0.035)
$Treat_i \times Post_{jt+1}$	0.017	0.019		
	(0.028)	(0.028)		
$Treat_i \times Post_{jt+2}$	-0.040	-0.035		
	(0.046)	(0.047)		
$Treat_i \times Post_{jt+3}$	-0.012	-0.012		
	(0.032)	(0.032)		
$Treat_i \times Post_{jt+5}$			-0.024	-0.015
			(0.029)	(0.031)
Observations	449,786	449,786	449,786	449,786
Adjusted R-squared	0.997	0.997	0.997	0.997
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	190	190	190	190
Regions	18375	18375	18375	18375

Notes: All HDI values are scaled (HDI×100). All columns include World Bank aid, leaders' birth regions, country-year, and regional fixed effects. Standard errors are clustered at the country-year and regional level and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

In Section 3, inspired by Christian and Barrett (2017), I graphically showed in Figure 1 that there were no hints pointing towards the presence of pre-trends systematically and differentially affecting any of the groups under study. In other words, both exploitable and

[43] To reduce clutter, I did not present the coefficients for the different control periods, yet details are available upon request. Note that, for instance, in the most comprehensive specification detailed in column 11, only the periods with $\tau = 6$ and $\tau = 7$ showed significant coefficients, the former being equal to -0.104% and the latter to 0.088%, which unfortunately does not completely rule out the presence of long-term time heterogeneity effects.

non-exploitable regions shared parallel trends in their human development indexes before the FTA's activation period. Following Goldsmith-Pinkham et al. (2020), Borusyak et al. (2018) and Borusyak and Hull (2020), I run some tests which include placebo activation periods, i.e., activation periods that correspond to the period pre-FTA, as in $Treat_i \times Post_{i,t+T}$. The placebo variables are not statistically significant and barely affect the efficiency of my main estimator. This suggests that there are indeed no pre-trends threatening the identification of my main effect.

Table 9 – Other Robustness Tests

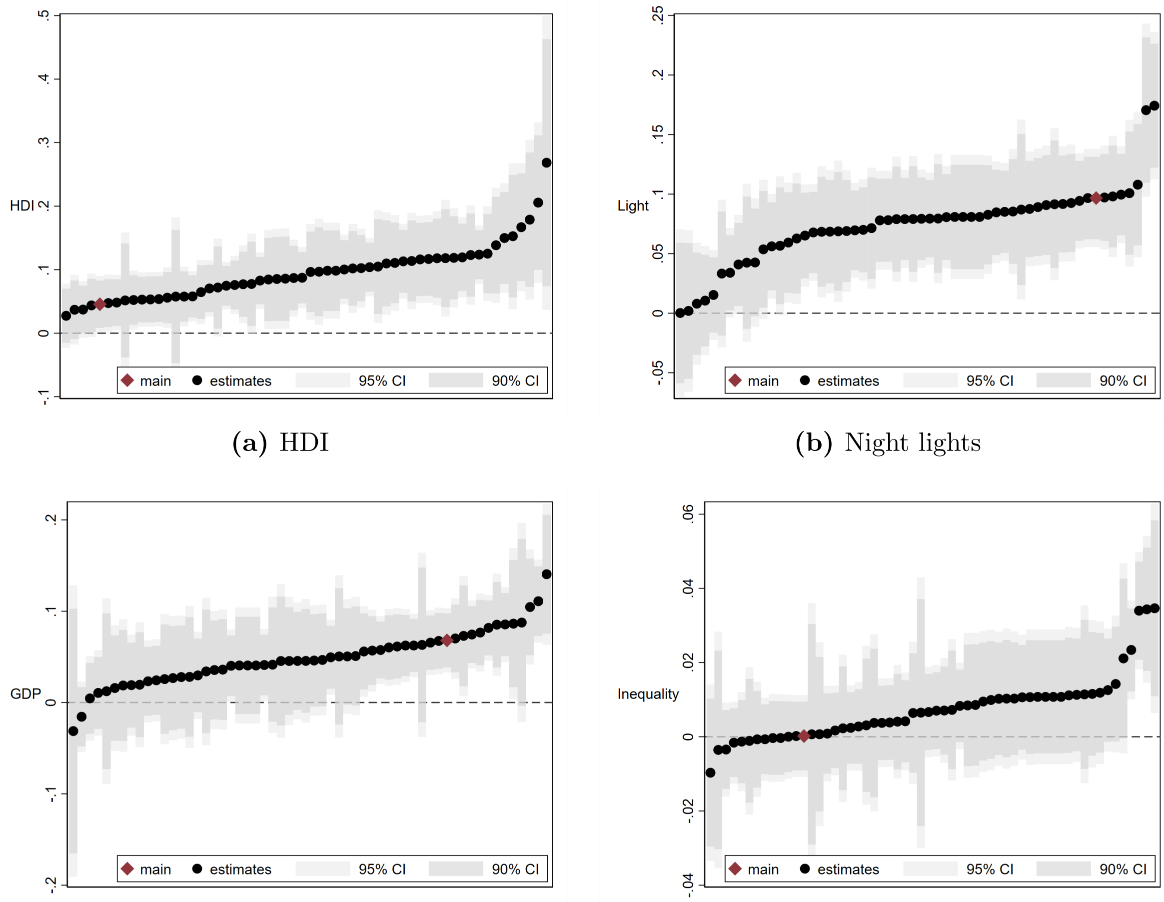
			Non-Exploitable region		55 km regions	
	(1)	(2)	(3)	(4)	(5)	(6)
	HDI	**HDI**	**HDI**	**HDI**	**HDI**	**HDI**
$Treat_i \times Post_{jt-5}$	0.098**	0.100**	0.097**	0.100**	0.035*	0.030***
	(0.039)	(0.046)	(0.038)	(0.046)	(0.021)	(0.022)
$Population(log)_{it-1}$		-0.0007		-0.0006		0.004
		(0.006)		(0.006)		(0.004)
Observations	238,453	200,116	220,421	182,365	940,881	721,266
Adjusted R-squared	0.998	0.997	0.997	0.997	0.999	0.999
Controls	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Countries	175	174	100	99	188	185
Regions	16719	15216	15499	14001	63504	53296

Notes: All HDI values are scaled (HDI×100). All columns include temperature, World Bank aid, leaders' birth regions, country-year, and regional fixed effects. Standard errors are clustered at the country-year and regional level and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

I conclude this section by conducting further robustness tests, shown in Table 9. For some, the lack of controls, beyond the use of the preferred set of fixed effects, could produce an omitted variable bias. I partly show that this does not seem to be the case in Tables 3 and 4, yet I run an additional test where, apart from including all geographic and political economy controls described before, a variable on population is also included (columns 2 and 4).[44] In the short-run, different levels of agglomeration in a region can impact its average access to goods and services and consequently inform its human development figures—e.g., high-conflict developing regions. Similarly, one can worry about the composition of the reference group in the sample of the main regression, and specifically on the lack of such reference for countries that only have exploitable land. For that reason, in columns 3 and 4 I only include countries in the main regression that have at least one non-exploitable region from which comparisons can be drawn directly.

[44]Moreover, in Appendix A I include all-controls versions of the main tables (Table A.12 and TableA.14) that do not directly use them in the central text. The results in these tests do not qualitatively change the conclusions drawn from the main tables.

As can be seen, there is no major change in relation to the main results of Table 3. Finally, in columns 5 and 6 I run tests on different sized subnational regions, as I now construct areas of 55 by 55 km (instead of the 111 km^2 used in my main specifications). Perhaps the preferred grid size used so far is still too large for the study of complex development indicators, as it could obscure the real effects of FTAs. However, the results are qualitatively comparable to the main results as the effects on HDI remain positive but small ($\approx$ 0.03 percentage points). The results for the different robustness tests of Table 9 indicate that neither the non-presence of non-exploitable regions in some countries, nor the inclusion of the variable that accounts for short-run agglomeration patterns, nor the size of my units of observation bias the main effects and, therefore, the preferred specifications explored in Tables 3 and 4 (in column 3) and from Tables 5 to 8 are robust.



(a) HDI **(b)** Night lights

(c) GDP **(d)** Inequality

Figure 7 – Summary of coefficients of interest

Notes: The figure shows the point estimates and their 90% and 95% confidence intervals for the main 4 variables studied in this chapter: HDI (scaled $\times$ 100)), night lights (log), GDP (log), and inequality. The graphs take into account all the tests explored in this chapter.

Finally, Figure 7 presents an overview of the multiple robustness tests (with/without controls, fixed effects, heterogeneity tests, trends tests, etc.) conducted in this study.

The estimates marked with red correspond to the main results from column 3 of Table 3, and columns 1, 3 and 5 of Table 4. As seen, for the majority of specifications, the effects evidenced earlier hold. That is, the effect of FTAs is positive but considerably small for HDI, positive for night lights and GDP, and rather statistically non-significant for inequality.

5 Conclusions

Trade agreements have been one of the most pervasive processes of economic globalization since the GATT meeting in 1947. The importance of trade agreements is not only defined by their ubiquity, but, more importantly, by their capacity to set the rules of the trade game. For instance, the adoption of Free Trade Agreements have remained a recurrent debate in developing and developed regions, as losing in the FTA game has been argued as a globally expected outcome. This potentially negative, global outcome, however, has not hindered the presence of FTAs worldwide. The relative number of more complex forms of FTAs has dramatically increased since 1990, and most economists would still argue that free trade vis-à-vis protectionism is a superior form of economic policy. The question then on why Free Trade Agreements are still a praised process of globalization, and yet provoke such backlash from heterogeneous regions worldwide, remains unanswered. In this paper I explored the impact of FTAs on both human and economic development at the subnational level in order to assess whether views about FTAs can be associated with particular effects of such trade policies on development.

My empirical approach made use of global, high spatial-resolution land cover data which describes the predominant type of land on the surface of subnational areas between 1992 and 2015, and a time-series (1990-2015) national-level proxy of FTAs' depth for a maximum of 207 countries. I interacted the naturally-determined land data with the FTAs indicator to exploit exogenous subnational variation over time, via a difference-in-differences design. My identifying assumption is that other than via the impact of Free Trade Agreements, and conditional on the use of relevant covariates such as country-year and regional fixed effects, development trends in subnational regions with and without naturally(exogenously)-determined land cover should have not been different. In other words, I relied on an identification strategy that used a conditionally exogenous interaction (treatment) to identify the effect of Free Trade Agreements at the subnational level.

My main results show that FTAs' local effect on human development is *small* yet *positive*. I argue that this rather small yet positive impact on human development is best explained by an increase of economic activity that does not alter inequality levels. I test such a mechanism in various ways and show that FTAs have a *positive* impact on economic activity, measured by increases of night light emissions and GDP, and have no impact on inequality, measured by a night light GINI index. I also show that, while for more unequal countries the effects of FTAs on human development are negative vis-à-vis more equal countries, their positive effects on economic activity remain mostly undifferentiated from the ones seen in more equal nations.

FTAs are agreements that involve provisions that differ from dyad to dyad, from agreement to agreement, and from sector to sector. Only focusing on the analysis of average effects would render a limited overview of the phenomenon. Therefore, I looked into impact heterogeneities inspired in such provisions. When looking into a *north-south* partner distinction, I show that while the effect of FTAs signed with countries of the north do have a smaller size, the effect is not statistically different from the one generated by FTAs signed with countries of the south. Also, I looked into the role of added complexity or depth to FTAs when including provisions beyond the usual elimination of tariffs and quotas and show that, while the impact of more complex/deeper FTAs is negative, such impact is not statistically different from that produced by less complex/shallower FTAs. Finally, as part of my main results, I explored sectoral heterogeneities of FTAs' impact. These estimates reveal that urban-associated productive regions perform comparatively better than any other exploitable region.

This work sheds light on the effects of FTAs on different indicators related to development. By doing so, it reconciles the impact of FTAs on human development with economic development by assessing the effects on economic activity and inequality patterns of such FTAs. Moreover, it uses information on most countries of the globe and thus is more generalizable than previous studies that used a limited number of countries with incomparable identification strategies. Moreover, it investigates the subnational effects of FTAs on development, a task in which this work is a pioneer, and that allows for the better understanding of local heterogeneities and causal mechanisms of the FTAs' phenomenon. For policy makers, this piece offers key lessons regarding the conformation and negotiation of FTAs, as it identifies characteristics about the partners, depths, and sectors which FTAs should focus on. More importantly, it offers lessons about the goal indicators to be stressed as tackling existing levels of inequality has been shown in this study to be key to translating increased levels of economic activity into increased levels of human development.

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Appendix

A Additional Tables

Table A.1 – Inverse Hyperbolic Sine Function

	(1)	(2)	(3)	(4)
VARIABLES	IHS GDP	IHS GDP	IHS Light	IHS Light
$Treat_i \times Post_{jt-5}$	0.069***	0.044*	0.083***	0.128***
	(0.016)	(0.026)	(0.013)	(0.023)
Observations	448,021	237,763	389,968	209,911
Adjusted R-squared	0.986	0.986	0.975	0.981
Controls	NO	YES	NO	YES
Country-Year FE	YES	YES	YES	YES
GRID FE	YES	YES	YES	YES
Countries	193	176	200	176
Regions	4991	2690	4399	2336

Notes: All columns include country-year and regional fixed effects. When specified, the set of controls includes temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.2 – Water regions as exploitable land

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times Post_{jt-5}$	0.110***	0.082***	0.039	0.013
	(0.041)	(0.029)	(0.036)	(0.010)
Observations	238,453	209,911	237,763	197,855
Adjusted R-squared	0.998	0.980	0.984	0.692
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	16719	16392	16722	16111

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3 – Land-changing regions excluded

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times Post_{jt-5}$	0.086**	0.079***	0.046	0.010
	(0.040)	(0.028)	(0.033)	(0.009)
Observations	228,124	200,695	227,475	189,081
Adjusted R-squared	0.997	0.980	0.984	0.691
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	15997	15672	16000	15397

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.4 – Local inequality and local development

	(1) **HDI**	(2) **Light**	(3) **HDI**	(4) **Light**	(5) **HDI**	(6) **Light**
$Treat_i \times Post_{jt-5}$	0.087***	0.068***	0.117***	0.069**	0.150***	0.101***
	(0.031)	(0.026)	(0.035)	(0.030)	(0.044)	(0.031)
$Treat_i \times Post_{jt-5} \times Inequality_{it-1}$	-0.070***	-0.026*				
	(0.016)	(0.015)				
$Treat_i \times Post_{jt-5} \times AvgIneq3y_{it}$			-0.092***	-0.023		
			(0.025)	(0.020)		
$Treat_i \times Post_{jt-5} \times AvgIneq5y_{it}$					-0.103***	-0.043**
					(0.034)	(0.021)
Observations	339,361	336,057	280,724	277,213	231,181	227,663
Adjusted R-squared	0.997	0.975	0.997	0.976	0.997	0.977
Controls	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Countries	184	185	184	185	184	185
Regions	17157	17169	17157	17167	17099	17025

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.5 – "Generalized" DID

VARIABLES	(1) HDI	(2) Light	(3) GDP	(4) Inequality
$Treat_i \times Post_{jt-5}$	0.048**	0.034*	0.011	0.007
	(0.022)	(0.019)	(0.024)	(0.006)
Observations	449,786	389,968	448,021	358,031
Adjusted R-squared	0.997	0.972	0.985	0.706
Controls	NO	NO	NO	NO
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	190	200	193	185
Regions	18375	18046	18400	17169

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.6 – Number of FTAs

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times FTANumber_{it-5}$	0.0003	-0.0004**	-0.0008***	0.0000
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Observations	238,453	209,911	237,763	197,855
Adjusted R-squared	0.9975	0.9804	0.9843	0.6925
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	16719	16392	16722	16111

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.7 – Depth of FTAs

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times FTADepth_{it-5}$	0.007 (0.007)	0.007 (0.005)	-0.006 (0.005)	0.003 (0.002)
Observations	238,453	209,911	237,763	197,855
Adjusted R-squared	0.998	0.980	0.984	0.692
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	16719	16392	16722	16111

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.8 – Big vs. Small countries

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times Post_{jt-5}$	0.208*	0.055	0.102	0.001
	(0.113)	(0.048)	(0.091)	(0.031)
$Treat_i \times Post_{jt-5} \times Big_{jt}$	-0.115	0.027	-0.064	0.010
	(0.114)	(0.047)	(0.086)	(0.031)
Observations	238,453	209,911	237,763	197,855
Adjusted R-squared	0.998	0.980	0.984	0.692
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	16719	16392	16722	16111

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.9 – Main results with comparable samples

	1992-2013				*Non-missing data*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HDI	**Light**	**GDP**	**Inequality**	**HDI**	**Light**	**GDP**	**Inequality**
$Treat_i \times Post_{jt-5}$	0.100***	0.081***	0.047	0.011	0.102**	0.085***	0.019	0.010
	(0.000)	(0.027)	(0.031)	(0.009)	(0.000)	(0.027)	(0.037)	(0.009)
Observations	206,047	209,911	205,702	197,855	178,159	178,159	178,159	178,159
Adjusted R-squared	0.998	0.980	0.985	0.692	0.997	0.980	0.980	0.693
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Countries	173	176	176	173	171	171	171	171
Regions	16555	16392	16568	16111	15899	15899	15899	15899

Notes: All HDI values are scaled (HDI×100). Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.10 – Inequality: Winsorized ranges

	(1) **LumenGini: Population split**	(2) **LumenGini: 0.10-0.90**	(3) **LumenGini: 0.20-0.80**	(4) **LumenGini: 0.201-0.659**
$Treat_i \times Post_{jt-5}$	0.015	0.013	0.015	0.017*
	(0.011)	(0.012)	(0.010)	(0.010)
$Treat_i \times Post_{jt-5} \times BigGrid_{it}$	-0.007			
	(0.009)			
Observations	197,855	75,177	52,381	43,283
Adjusted R-squared	0.693	0.402	0.550	0.478
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	173	163	157	154
Regions	16111	8431	7565	6687

Notes: All columns include country-year and regional fixed effects. When specified, the set of controls includes temperature, World Bank aid, leaders' birth regions. Column 1 also controls for the $BigGrid_{it}$ dummy. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.11 – Inequality and GDP

	Local Inequality	*Historic Inequality*	*Year-to-year Inequality*	*LAC vs.* The World	*Henderson's Early-Late* Adjusted	*Henderson's Early-Late:*
	(1)	(2)	(3)	(4)	(5)	(6)
	GDP	**GDP**	**GDP**	**GDP**	**GDP**	**GDP**
$Treat_i \times Post_{jt-5}$	0.019	0.086***	0.105***	0.082***	0.056**	0.111***
	(0.028)	(0.021)	(0.032)	(0.018)	(0.025)	(0.023)
$Treat_i \times Post_{jt-5} \times AvgIneq3y_{it}$	-0.041**					
	(0.018)					
$Treat_i \times Post_{jt-5} \times Unequal_j$		-0.038				
		(0.037)				
$Treat_i \times Post_{jt-5} \times Unequal_{jt}$			-0.058			
			(0.050)			
$Treat_i \times Post_{jt-5} \times LAC_j$				-0.257***		
				(0.081)		
$Treat_i \times Post_{jt-5} \times LateDev_j$					0.089**	-0.033
					(0.035)	(0.035)
Observations	278,790	408,193	192,765	448,021	302,883	302,883
Adjusted R-squared	0.977	0.983	0.982	0.985	0.983	0.983
Country-Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Countries	184	157	143	193	116	116
Regions	17157	16731	16330	18400	12346	12346

Notes: GDP values are logged. All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.12 – FTAs impact heterogeneity on HDI with all controls

	(1) **FTAs North-South**	(2) **FTAs Conditionality**	(3) **Conditionality: Number FTAs**	(4) **Sectoral Heterogeneity**
$Treat_i \times PostSouth_{jt-5}$	0.118***			
	(0.030)			
$Treat_i \times PostNorth_{jt-5}$	-0.009			
	(0.050)			
$Treat_i \times Post_{jt-5}$		0.268**	0.0002	0.077*
		(0.118)	(0.0003)	(0.040)
$Treat_i \times Post_{jt-5} \times ComplexFTA_{it-5}$		-0.207*	0.0015	
		(0.120)	(0.0028)	
$Treat_i \times Post_{jt-5} \times Agriculture_i$				0.137***
				(0.051)
$Treat_i \times Post_{jt-5} \times ManuServ_i$				0.106
				(0.069)
Observations	238,453	238,453	238,453	238,453
Adjusted R-squared	0.998	0.998	0.9975	0.998
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	175	175	175
Regions	16719	16719	16719	16719

Notes: All HDI values are scaled (HDI×100). All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.13 – North vs. South

	(1) **HDI**	(2) **Light**	(3) **GDP**	(4) **Inequality**
$Treat_i \times PostSouth_{jt-5}$	0.108***	0.027	0.038	0.014
	(0.029)	(0.026)	(0.030)	(0.010)
$Treat_i \times PostNorth_{jt-5}$	-0.002	0.064**	0.010	-0.002
	(0.049)	(0.031)	(0.043)	(0.010)
Observations	238,453	209,911	237,763	197,855
Adjusted R-squared	0.998	0.980	0.984	0.692
Controls	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Countries	175	176	176	173
Regions	16719	16392	16722	16111
North vs. South (p-value)	0.06	0.46	0.66	0.431

Notes: All HDI values are scaled (HDI×100), Light and GDP are logged. All columns include country-year and regional fixed effects, and control for temperature, World Bank aid, Leaders' birth regions. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.14 – Mechanism: Inequality with all controls

	Local Inequality		*Historic Inequality*		*Year-to-year Inequality*		*Henderson's Early-Late*		*Henderson's Early-Late: Adjusted*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	HDI	**Light**	**HDI**	**Light**	**HDI**	**Light**	**HDI**	**Light**	**HDI**	**Light**
$Treat_i \times Post_{jt-5}$	0.167***	0.108***	0.206***	0.087**	0.118**	0.000	0.052	0.042	0.116***	0.008
	(0.051)	(0.031)	(0.064)	(0.039)	(0.047)	(0.036)	(0.054)	(0.034)	(0.035)	(0.026)
$Treat_i \times Post_{jt-5} \times AvgIneq3y_{it}$	-0.121***	-0.045**								
	(0.031)	(0.022)								
$Treat_i \times Post_{jt-5} \times Unequal_j$			-0.206***	-0.009						
			(0.077)	(0.054)						
$Treat_i \times Post_{jt-5} \times Unequal_{jt}$					-0.073*	0.054*				
					(0.041)	(0.031)				
$Treat_i \times Post_{jt-5} \times LateDev_j$							0.025	0.053	-0.067	0.092**
							(0.071)	(0.048)	(0.054)	(0.041)
Observations	181,224	174,491	228,251	200,866	127,001	112,523	168,947	147,822	168,947	147,822
Adjusted R-squared	0.997	0.998	0.998	0.981	0.997	0.979	0.997	0.984	0.997	0.984
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Countries	171	171	152	153	130	128	115	115	115	115
Regions	15907	15801	15994	15663	14755	14150	11836	11588	11836	11588

Notes: LAC computations are not included due lack of variation. All HDI values are scaled (HDI×100), Light values are logged. All columns include country-year and regional fixed effects. Standard errors are clustered at the country-year and regional level, and are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.15 – Trade and GDP: Country level

VARIABLES	(1) Total Trade	(2) Total Trade
GDP_WB	0.417***	
	(0.033)	
GDP_GIS		0.404***
		(0.060)
Observations	3,994	3,994
Adjusted R-squared	0.968	0.944
Countries	115	115
Controls	YES	YES
Country FE	YES	YES
Year FE	YES	YES

Notes: Column (1) use data of the World Bank indicators database. Column (2) uses GDP geo-referenced information of Kummu et al. (2019) that was aggregated at the national level. All columns include logged population, country and year fixed effects. Standard errors are clustered at the country and year level, and are detailed in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.16 – Night lights, population and light inequality

VARIABLES	Inequality	Inequality
Light (log)	-0.051***	
	(0.0002)	
Population (log)		-0.033***
		(0.0002)
Observations	358,432	316,289

Notes: Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B Variable Descriptives

Table B.1 – Variables and sources

Variable	**Definition**	**Source**
HDI	Average human development index in region i times 100.	Own construction based on Kummu et al. (2018)
Light	The logarithm of the yearly average of night-light emissions within region i.	NOAA (2015)
Light (IHS)	The inverse hyperbolic sine of the yearly average of night-light emissions within region i.	NOAA (2015)
GDP	The logarithm of the yearly average of GDP within region i.	Kummu et al. (2018)
Inequality	Gini-like coefficient that represents the yearly distribution of nightlight among the population within region i.	Own generation based on the work by Elvidge et al. (2012)
Treat	Dummy=1 indicating if region i has, predominantly, exploitable land.	Own construction based on ESA (2017)
Agriculture	Dummy=1 indicating if region i has, predominantly, agricultural land.	Own construction based on ESA (2017)
ManuServ	Dummy=1 indicating if region i has, predominantly, urban land.	Own construction based on ESA (2017)
Other	Dummy=1 indicating if region i has, predominantly, other exploitable land.	Own construction based on ESA (2017)
Post	Dummy=1 if country j in year t is in the post-FTA's treatment period.	Own construction based on Dür et al. (2014)
PostNorth	Dummy=1 if country j in year t is in the post-FTA's treatment period, considering only FTAs signed with early-developed countries (as defined by Henderson et al., 2018).	Own construction based on Dür et al. (2014)
PostSouth	Dummy=1 if country j in year t is in the post-FTA's treatment period, considering only FTAs signed with late-developed countries (as defined by Henderson et al., 2018).	Own construction based on Dür et al. (2014)
Post (number)	Total number of FTAs that country j has signed in year t.	Own construction based on Dür et al. (2014)
Complex	Dummy=1 if country j in year t has signed on average FTAs with provisions beyond tariffs and quotas.	Own construction based on Dür et al. (2014)
ComplexFTA (number)	Total number of FTAs with provisions beyond tariffs and quotas that country j has signed in year t.	Own construction based on Dür et al. (2014)
Unequal	Dummy=1 if country j is above the historic world median of income inequality, measured by the income GINI.	Own construction based on World Bank (2020)
Unequal (year)	Dummy=1 if country j is above the yearly world median of income inequality, measured by the income GINI. income GINI.	Own construction based on World Bank (2020)
LAC	Dummy=1 if country j is Latin-American.	Own construction
LateDeveloped	Dummy=1 if country j is considered late-developed in Henderson et al. (2018).	Henderson et al. (2018)
LateDeveloped (adj.)	Dummy=1 if country j is in Henderson et al. (2018) sample and is above the historic median of inequality.	Own construction based on Henderson et al. (2018) and World Bank (2020)
Big	Dummy=1 if country j is above the yearly world median of GDP.	Own construction based on World Bank (2020)
Leader	Yearly dummy indicating whether the presidential leader of country j was born within region i.	Hodler and Raschky (2014)
WB Aid	The yearly disbursed World Bank aid in region i.	AidData (2017)
Temperature	Yearly mean temperature in region i.	Tollefsen et al. (2012)
Distance to Capital	The average distance in kilometers to capital city from region i.	Tollefsen et al. (2012)
Population (log)	The logarithm of the total, yearly population in region i.	Goldewijk et al. (2010, 2011)

Table B.2 – Descriptive Statistics

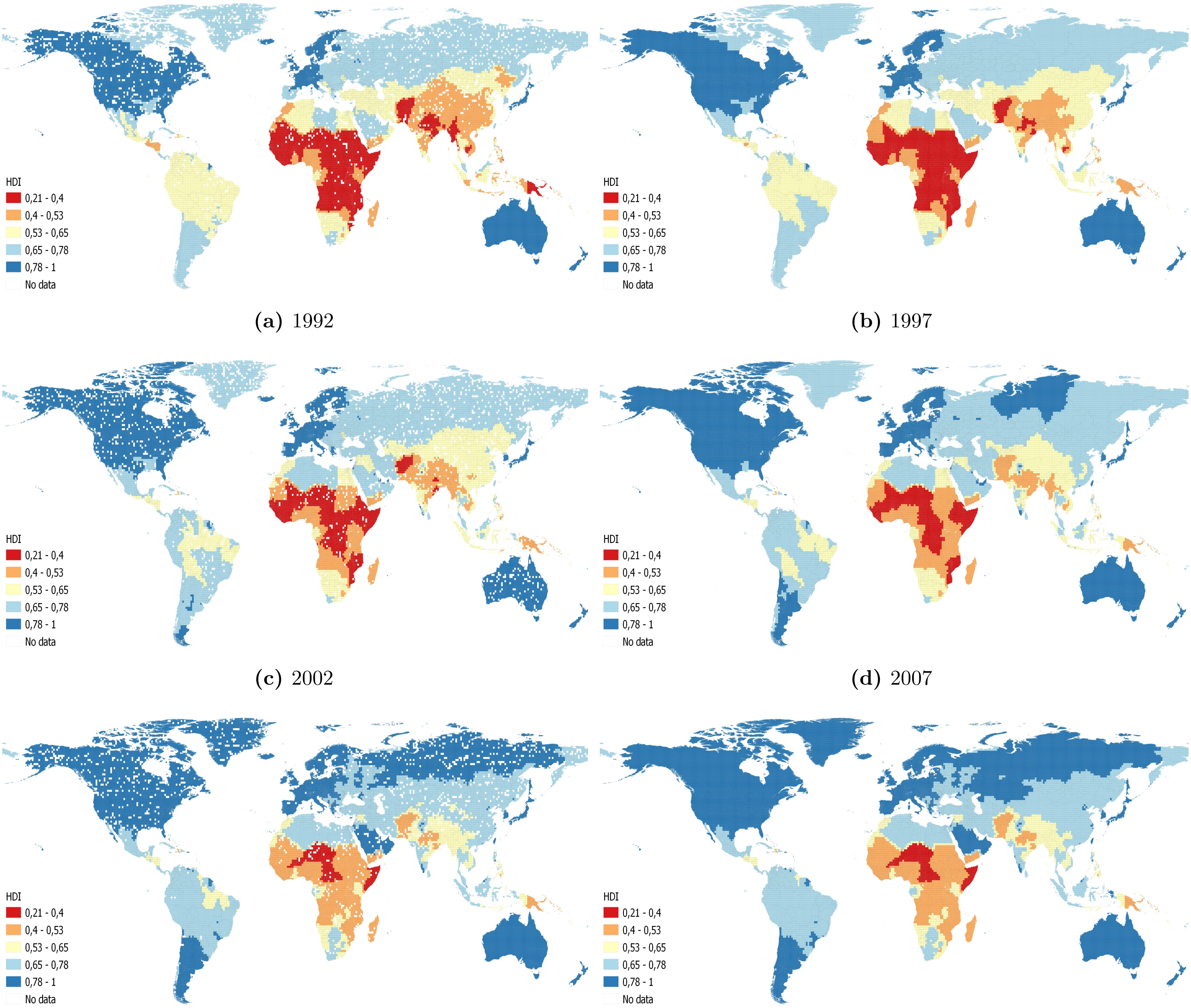
	N	Mean	S.D.	Min	Max
HDI	449,786	70.57	16.00	20.80	100
Light	356,464	-2.181	2.507	-4.605	4.141
Light (IHS)	356,464	0.619	0.998	0	4.834
GDP	422,951	11.10	7.701	-4.605	24.22
GDP (IHS)	422,951	12.46	6.361	0	24.92
Inequality	339,121	0.654	0.389	0	1.000
Treat	449,786	0.813	0.390	0	1
Agriculture	449,786	0.0839	0.277	0	1
ManuServ	449,786	0.00133	0.0364	0	1
Other	449,786	0.728	0.445	0	1
Post	449,786	0.548	0.498	0	1
PostNorth	449,786	0.494	0.500	0	1
PostSouth	449,786	0.323	0.468	0	1
Post (number)	449,786	2.968	1.426	0	154
Complex	449,786	0.467	0.499	0	1
ComplexFTA (number)	449,786	1.621	7.053	0	100
Unequal	409,862	0.612	0.487	0	1
Unequal (year)	194,714	0.611	0.487	0	1
LAC	449,786	0.113	0.316	0	1
LateDeveloped	304,221	0.4791418	.4995656	0	1
LateDeveloped (adj.)	304,221	0.6731225	.4690728	0	1
Big	449,786	0.836	0.370	0	1
Leader	449,786	0.00535	0.0730	0	1
WB Aid	449,786	56,477.88	1,206,681	0	2.85e+08
Temperature	238,538	10.600	13.922	-24.619	55.993
Distance to capital	420,262	1,753	1,616	13.92	7,942
Population (log)	360,104	5.019	3.498	-10.54	14.25

Table B.3 – Land Cover categories

NB_LAB	LC Label	NB_LAB	LC
0	No data	110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
10	Cropland, rainfed	120	Shrubland
11	Herbaceous cover	121	Shrubland evergreen
12	Tree or shrub cover	122	Shrubland deciduous
20	Cropland, irrigated or post-flooding	130	Grassland
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	140	Lichens and mosses
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)	150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	151	Sparse tree (<15%)
60	Tree cover, broadleaved, deciduous, closed to open (>15%)	152	Sparse shrub (<15%)
61	Tree cover, broadleaved, deciduous, closed (>40%)	153	Sparse herbaceous cover (<15%)
62	Tree cover, broadleaved, deciduous, open (15-40%)	160	Tree cover, flooded, fresh or brakish water
70	Tree cover, needleleaved, evergreen, closed to open (>15%)	170	Tree cover, flooded, saline water
71	Tree cover, needleleaved, evergreen, closed (>40%)	180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water
72	Tree cover, needleleaved, evergreen, open (15-40%)	190	Urban areas
80	Tree cover, needleleaved, deciduous, closed to open (>15%)	200	Bare areas
81	Tree cover, needleleaved, deciduous, closed (>40%)	201	Consolidated bare areas
82	Tree cover, needleleaved, deciduous, open (15-40%)	202	Unconsolidated bare areas
90	Tree cover, mixed leaf type (broadleaved and needleleaved)	210	Water bodies
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	220	Permanent snow and ice

Note: Taken from Land Cover ESACCI-LC-Legend datafile (ESA CCI, 2017)

C Visual Descriptives



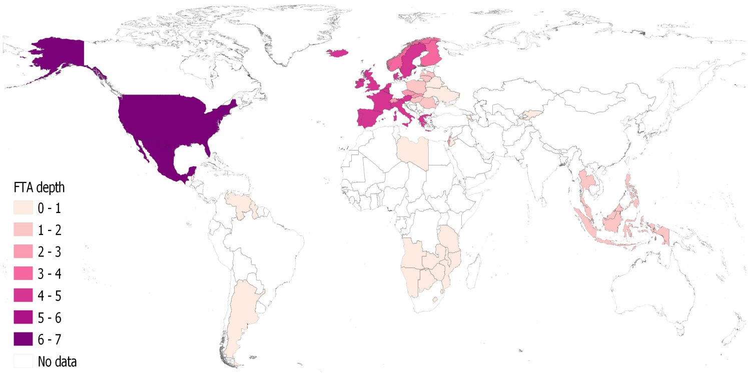
(a) 1992 **(b)** 1997

(c) 2002 **(d)** 2007

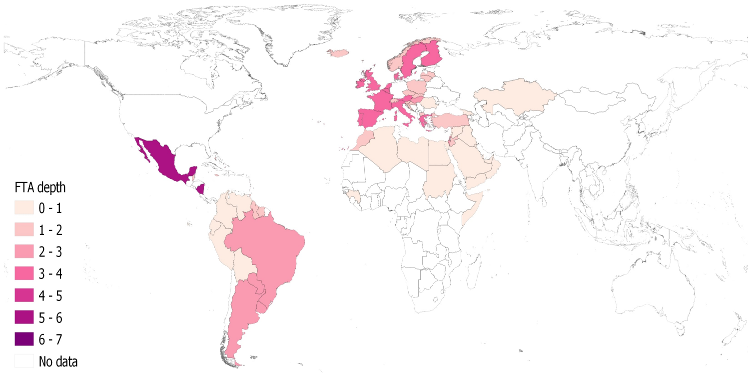
(e) 2012 **(f)** 2013

Figure C.1 – Gridded HDI over time

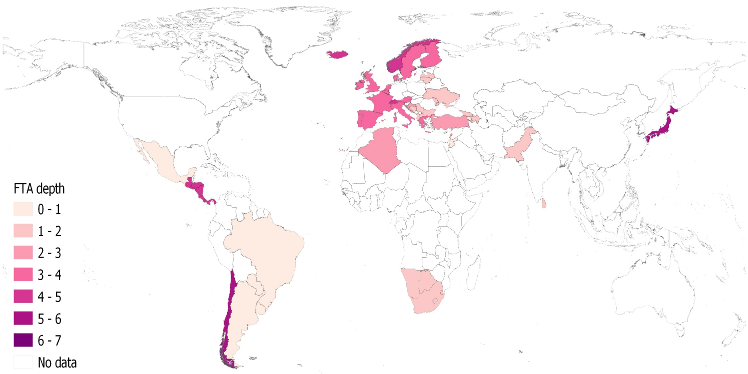
Notes: The dimensions of grids are of, roughly, 111 km by 111 km. The grids are clipped to land, at the ADM1 level.



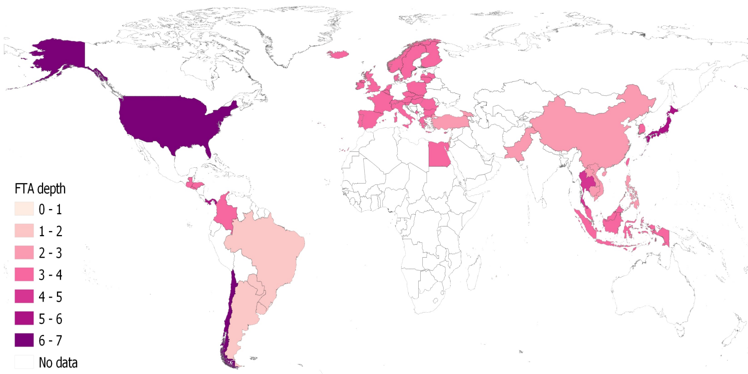
(a) 1992



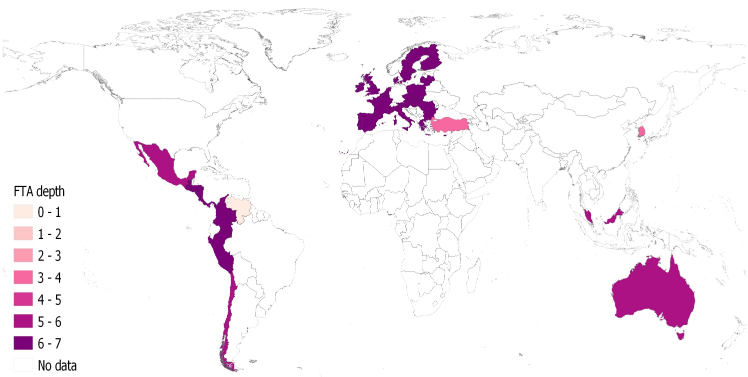
(b) 1997



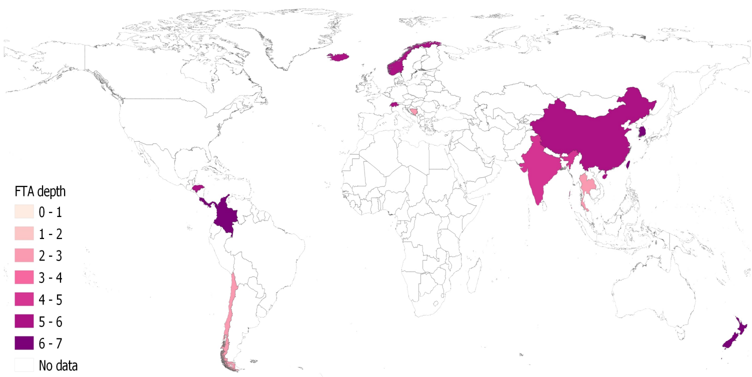
(c) 2002



(d) 2007



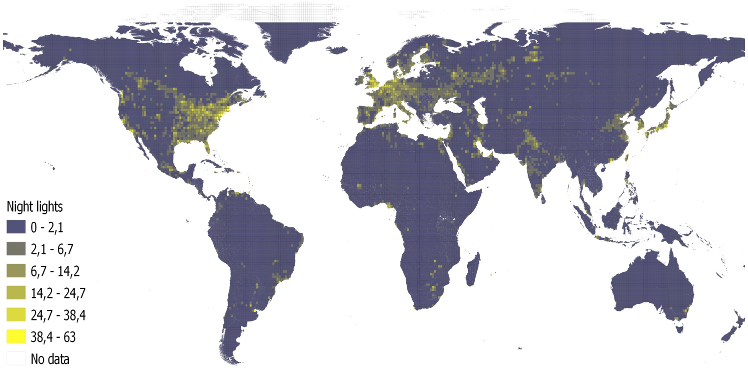
(e) 2012



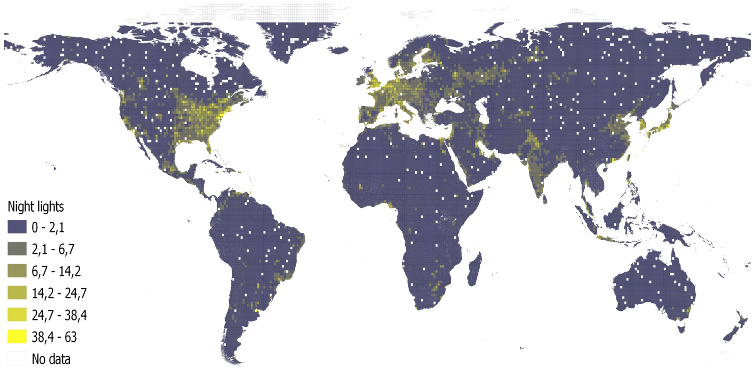
(f) 2013

Figure C.2 – Gridded FTA depth over time

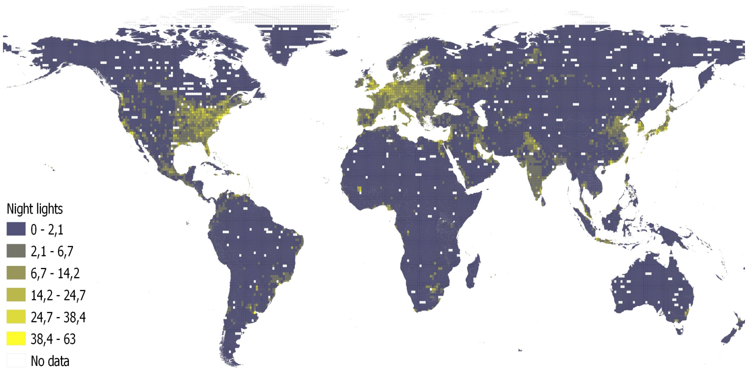
Notes: The dimensions of grids are of, roughly, 111 km by 111 km. The grids are clipped to land, at the ADM1 level.



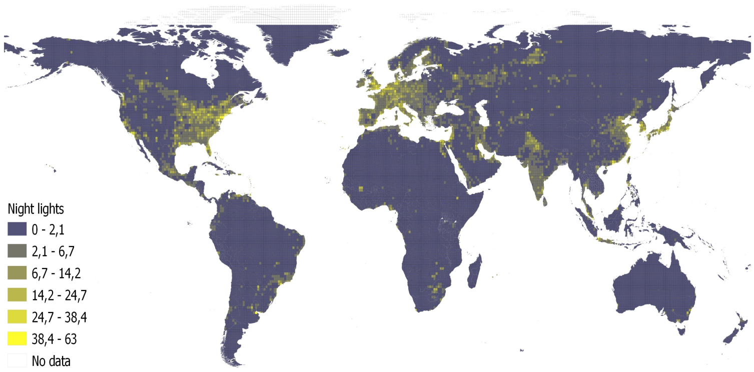
(a) 1992



(b) 1997



(c) 2002



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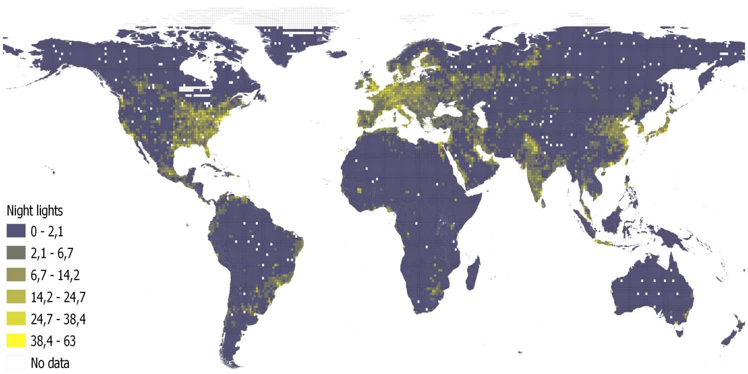

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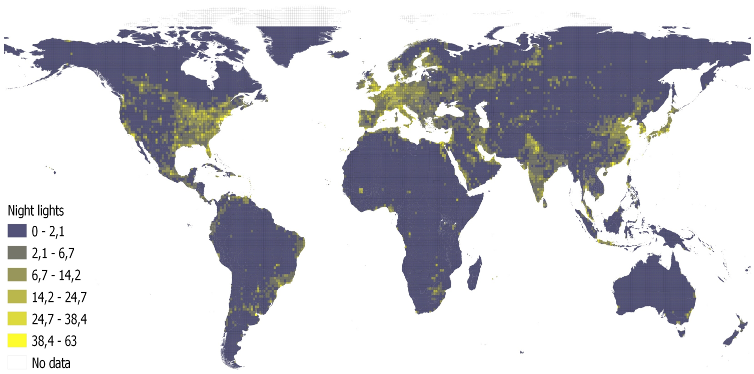
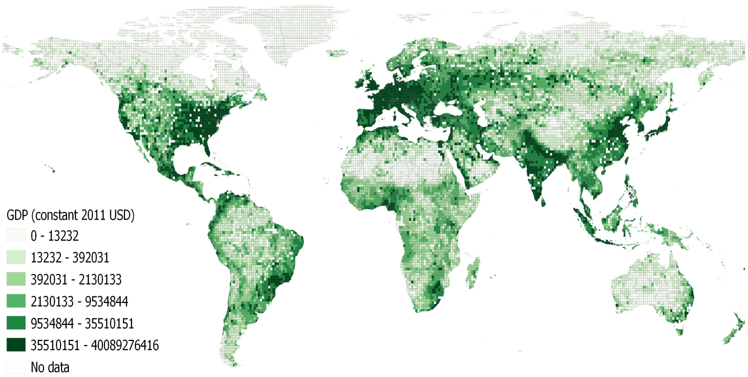


(f) 2013

Figure C.3 – Gridded night lights over time

Notes: The dimensions of grids are of, roughly, 111 km by 111 km. The grids are clipped to land, at the ADM1 level.



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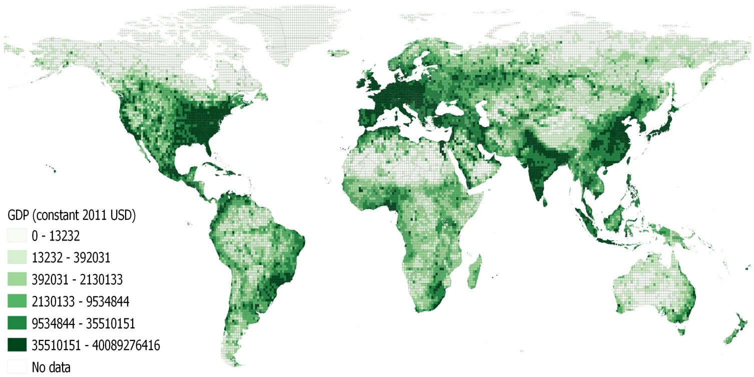
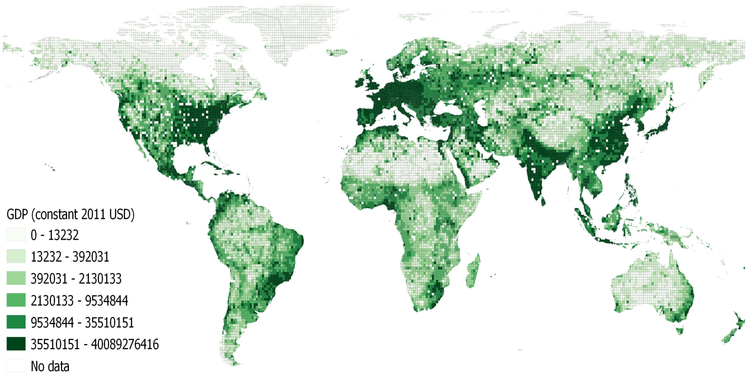
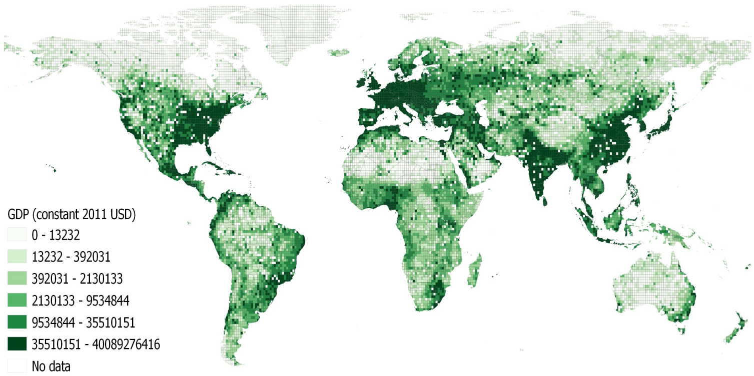


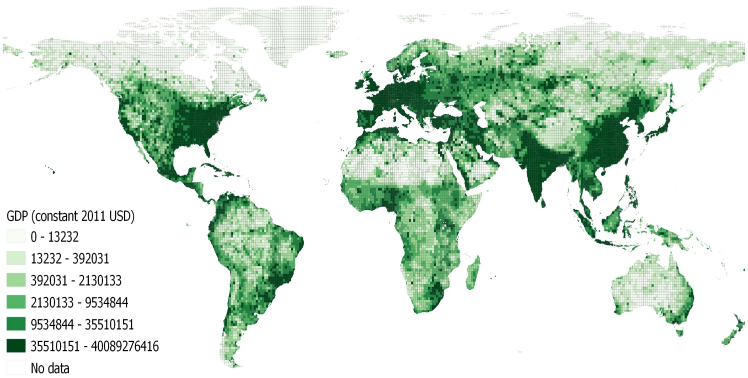
(b) 1997



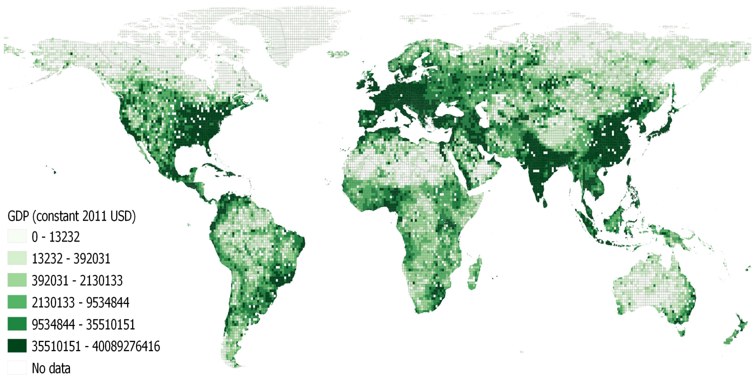
(c) 2002



(d) 2007



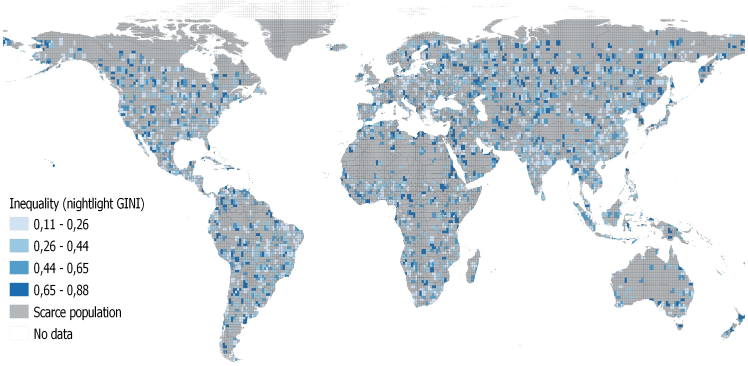
(e) 2012



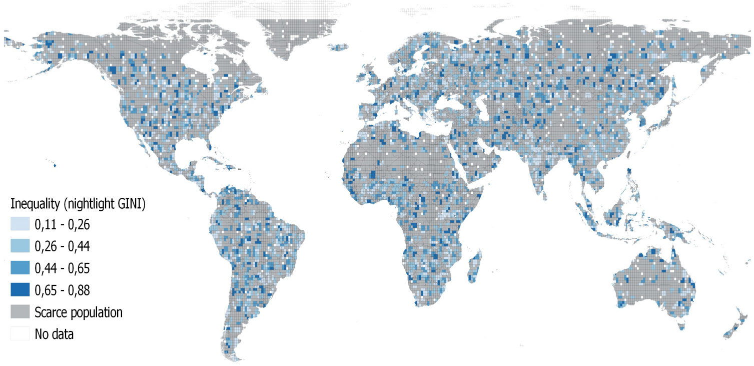
(f) 2013

Figure C.4 – Gridded GDP over time

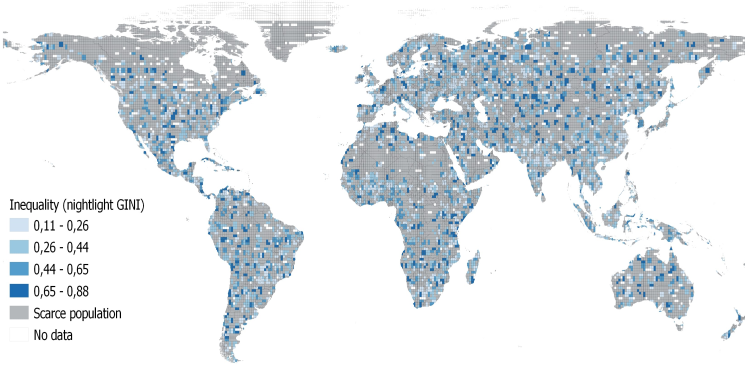
Notes: The dimensions of grids are of, roughly, 111 km by 111 km. The grids are clipped to land, at the ADM1 level.



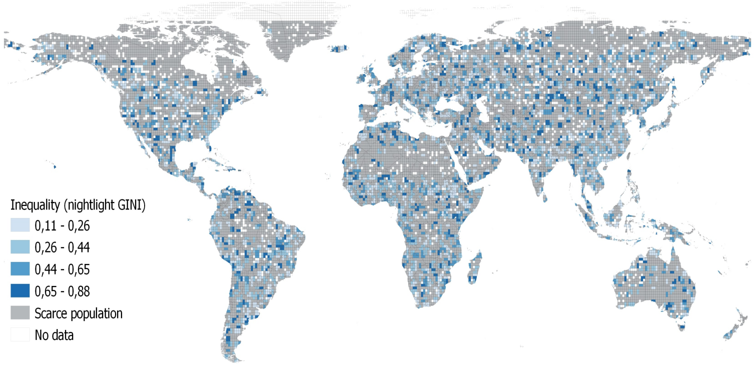
(a) 1992



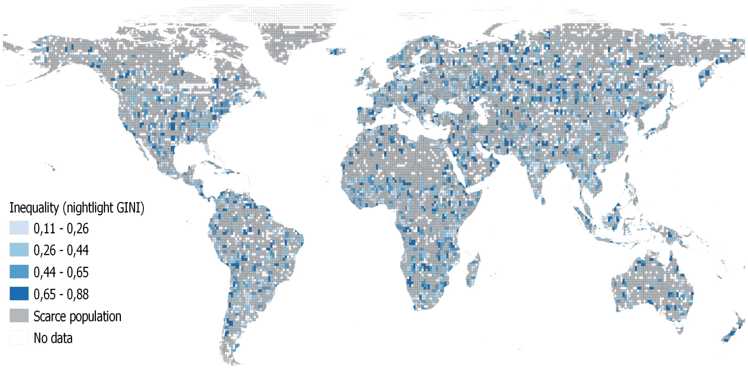
(b) 1997



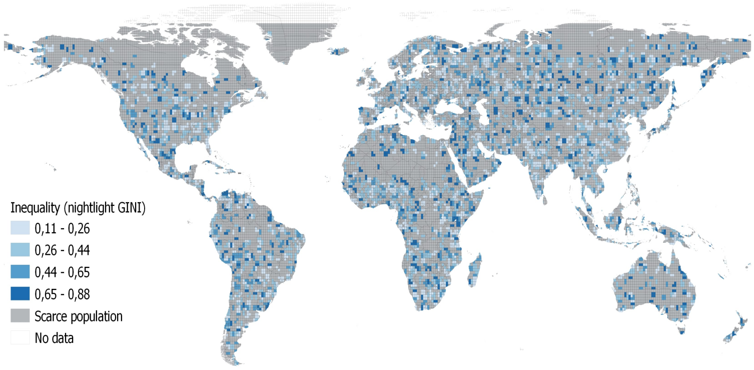
(c) 2002



(d) 2007



(e) 2012

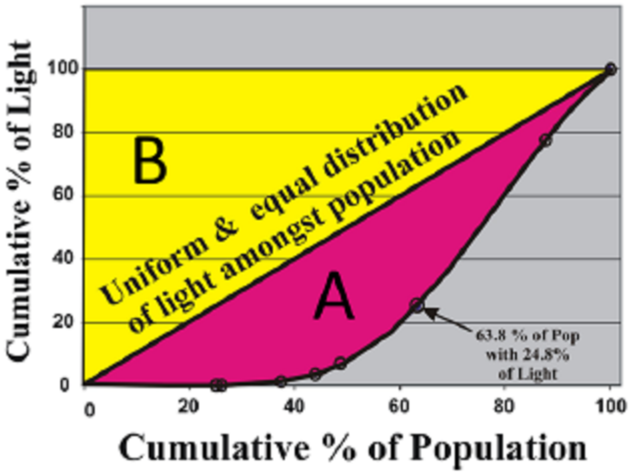


(f) 2013

Figure C.5 – Gridded inequality over time

Notes: The dimensions of grids are of, roughly, 111 km by 111 km. The grids are clipped to land, at the ADM1 level.

C.1 Additional Figures



Notes: Graph drawn from Elvidge et al. (2012) pp.25. This local quasi-GINI coefficient ranges between 0 and 1 as a result of the ratio A/B, where A is the area between the line of perfect equality (diagonal) and a Lorenz curve that plots the cumulative distribution of night lights against the cumulative distribution of population, and B, which quantifies the area above the diagonal of perfect equality (being this area equal to 0.5).

Figure C.1 – Inequality of night light

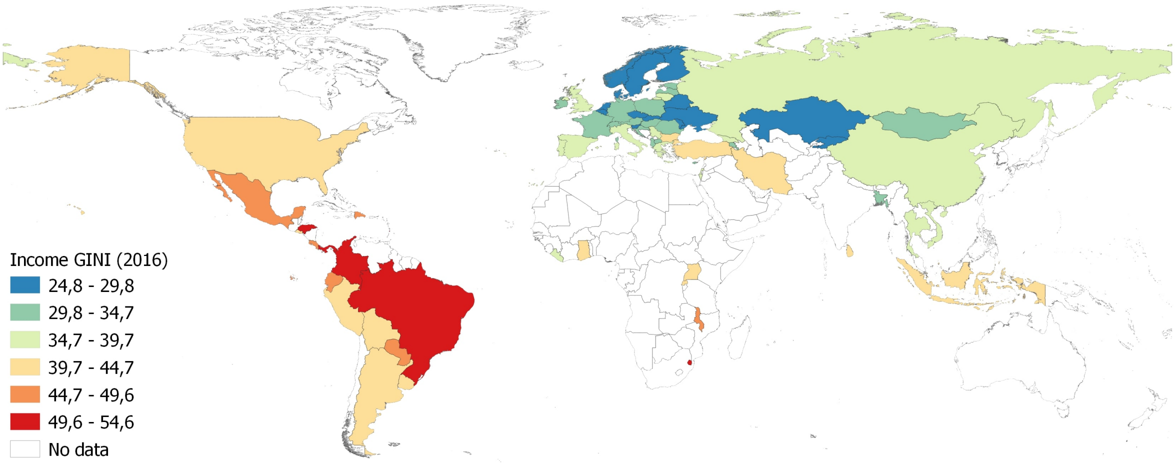


Figure C.2 – Inequality Map for 2016

Notes: The figure shows the income GINI coefficients per country for the year 2016. The GINI coefficient is an indicator of inequality that ranges between 0 and 1, where the closest to 1 is more unequal and the closest to 0 the more equal.