IDB WORKING PAPER SERIES Nº IDB-WP-00935

Bright investments: Measuring the impact of transport infrastructure using luminosity data in Haiti

Oscar A. Mitnik
Raul Sanchez
Patricia Yañez-Pagans

Inter-American Development Bank
Office of Strategic Planning and Development Effectiveness

IDB Invest - Strategy and Development Department

December 2018

Bright investments: Measuring the impact of transport infrastructure using luminosity data in Haiti

Oscar A. Mitnik
Raul Sanchez
Patricia Yañez-Pagans

December 2018

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Mitnik, Oscar Alberto.
Bright investments: measuring the impact of transport infrastructure using luminosity data in Haiti / Oscar A. Mitnik, Raul Sanchez, Patricia Yáñez.
p. cm. — (IDB Working Paper Series ; 935)
Includes bibliographic references.
1. Electric lighting-Haiti. 2. Transportation-Haiti-Finance. 3. Infrastructure (Economics)-Haiti-Finance. I. Sanchez, Raul. II. Yáñez, Patricia. III. Inter-American Development Bank. Office of Strategic Planning and Development Effectiveness. IV. IDB Invest. V. Title. VI. Series.
IDB-WP-935

http://www.iadb.org

1300 New York Ave NW, Washington DC 20577

Bright investments: Measuring the impact of transport infrastructure using luminosity data in Haiti [*]

Oscar A. Mitnik[†] Raul Sanchez[‡] Patricia Yañez-Pagans[§]

December 2018

Abstract

This paper quantifies the impacts of transport infrastructure investments on economic activity in Haiti, using satellite night-light luminosity as a proxy measure. Our identification strategy exploits the differential timing of rehabilitation projects across various road segments of the primary road network. We combine multiple sources of non-traditional data and carefully address concerns related to unobserved heterogeneity. The results obtained across multiple specifications consistently indicate that receiving a road rehabilitation project leads to an increase in luminosity values of between 6% and 26% at the communal section level. Taking into account the national level elasticity between luminosity values and GDP, we approximate that these interventions translate into communal section-GDP increases of between 0.5% and 2.1%, for communal sections benefited by a transport infrastructure project. We observe temporal and spatial variation in results, and crucially that the larger impacts appear once projects are completed and are concentrated within 2 km buffers around the intervened roads. Neither the richest or the poorest communities reap the benefits from road improvements, with gains accruing to those in the middle of the ranking of communal sections, based on unsatisfied basic needs. Our findings provide novel evidence on the role of transport investments in promoting economic activity in developing countries.

Keywords: Haiti; night-time luminosity, road investments

JEL codes: O1; O47; R4; D04

[*]We thank useful comments and suggestions from two anonymous IDB reviewers, Eduardo Cavallo, Rene Cortes, Marco Gonzalez-Navarro, Pablo Guerrero, Manuel Pastor, Maja Schling, Adam Storeygard, and from participants in presentations at CAF, IDB, IDB Invest, and the Annual LACEA Meetings. We also thank Naijun Zhou for his work in pre-processing some of the satellite data.

[†]Inter-American Development Bank and IZA. Email: omitnik@iadb.org.

[‡]IDB Invest. Email: rsanchez@iadb.org.

[§]IDB Invest. Email: patriciaya@iadb.org.

1 Introduction

Roads can have an important role in alleviating poverty (Gertler et al., 2014; Gonzalez-Navarro and Quintana-Domeque, 2016). By reducing isolation, better roads should increase the accessibility to basic services (such as health and education), and to markets and employment centers, thus helping to reduce vulnerability and income variability (van de Walle and Cratty, 2002). Despite several studies about the effects of road improvements on socio-economic outcomes, there is still limited evidence for Latin America and the Caribbean (LAC) countries. There is even less evidence in highly poor and vulnerable settings where data limitations make it difficult to conduct rigorous causal analyses.

In this paper we exploit night-light satellite luminosity data, as well as detailed historical administrative information, to evaluate the impact of transport investments on economic activity in Haiti. In recent years a growing number of studies have relied on non-traditional sources of data for impact evaluation purposes (Alix-Garcia et al., 2015; Khanna, 2016; Gendron-Carrier et al., 2018). Micro-satellite data holds particular promise given the availability of historical information, ample geographic coverage, and its granularity. For these reasons, it is increasingly being used for poverty mapping and economic analysis (IPA, 2016). Yet the potential of satellite data cannot be realized without overcoming substantial technical challenges, that we highlight and address in this study.

The case of Haiti is quite unique. It is the poorest country in the Western Hemisphere, with 59% of the population living below the poverty line (The World Bank, 2012). The country also faces deep regional economic imbalances, with 75% of the rural population being poor (UNDP, 2013) and with its capital, Port-au-Prince, accounting for 80% of the country's industrial, commercial, and financial activities. Fostering economic development outside of the capital has been a priority of Haiti's government, and of multilateral development organizations working in the country. Road improvements are deemed as fundamental mechanisms that can help attain this objective, as road transport is the leading mode of transportation for cargo and passengers in the country.

In 2010, Haiti experienced one of the strongest earthquakes in its history leaving almost three million people affected and large economic losses (CBS, 2010; Cavallo et al., 2010). This event spurred an unprecedented program of foreign financial assistance to help rebuild the country's infrastructure and to promote economic development. Between 2010 and 2014, US$13.5 billion dollars had been invested or pledged for the country by multiple international organizations and through private charitable contributions (U.S. Congress, 2014), roughly twice the size of the country's GDP in 2010 (The World Bank, 2018).[1] Despite the large dependence on financial aid, and the need for robust empirical evidence to better guide policy making, almost no rigorous impact evaluation studies have been conducted on the country, which is partly due to the limited availability of statistical information, and difficulty and cost of producing them (CEPR, 2012).

The main objective of this paper is to quantify the impacts of transport infrastructure investments on economic activity in Haiti, proxied by night-time satellite luminosity data (from now on referred as luminosity). For this, we generate a novel geo-referenced panel data set for the country, exploiting multiple sources of satellite information, secondary data, and detailed historical administrative information on infrastructure interventions in Haiti's national road network, which have been funded by multilateral development institutions between 2004 and 2013.[2] We take advantage of the differential timing of road rehabilitation projects and compare changes in luminosity occurring in buffers around road segments that received a rehabilitation project ("treated") versus those observed around segments that did not receive an intervention ("controls"). We estimate a variety of fixed-effects models at the communal section and pixel-level and conduct multiple robustness and placebo checks to reduce any concerns of unobserved heterogeneity.

Although there are prior studies addressing the link between road infrastructure and economic activity, there are still relatively few papers that rigorously establish causal links, and the majority of them have been concentrated in developed countries or in Asian or African countries. Among these papers, early work by Chandra and Thompson (2000) exploits county-level industry data to show that counties next to a US Interstate Highway increase their level of economic activity, while those adjacent counties not directly on the highway see a decrease in economic activity. Datta (2012) and Ghani et al. (2016) evaluate the upgrade of a central highway network in India, finding that manufacturing grows disproportionately along the road network and that firms close to improved roads reduce their average stock on inventories and re-optimize their choice of suppliers. Banerjee et al. (2012) find

[1] Only taking into account multilateral or direct country aid, Haiti received disbursements for US$8.4 billion from 2011 to 2016 (IDB, 2017).

[2] Given the availability of data, we focus on interventions from the Inter-American Development Bank, the World Bank, and the European Union.

that road construction in Indian villages results in greater access to government services, lower consumer prices, higher agricultural prices, increased employment outside of agriculture and less daily migration. Casaburi et al. (2013) show that village feeder roads in Sierra Leone contribute to reduce market prices of local agricultural goods.

The use of luminosity data is relatively recent in the economics field and follows the work of Henderson et al. (2012) that shows that country-level mean light intensities are a good proxy for GDP. In the transport sector, Storeygard (2016) uses city-level luminosity values, interacted with global oil price shocks and distances to the nearest port, to show that there is a significant inverse relationship between transport costs and urban economic output in multiple African countries. Gonzalez-Navarro and Quintana-Domeque (2016) show a more dispersed distribution of luminosity data in cities that have implemented subway systems suggesting a decentralization of economic activity. Alder (2017) uses a general equilibrium trade framework to compare the transport network configuration strategy followed by India, of building a highway connecting the four largest economic centers of the country (Golden Quadrilateral), versus the Chinese strategy, of connecting intermediate-sized cities. Using district-level data he finds that the Chinese strategy can lead to further gains and less unequal effects in economic activity when compared to the Indian strategy. Finally, Khanna (2016) explores the impacts on economic activity of transport infrastructure investments in the Golden Quadrilateral of India. Connecting nodal cities with straight lines as instruments for the endogenous placement of road networks he shows evidence of spatial spillovers as a result of road investments using luminosity data.

Despite the increased popularity of satellite imagery in recent research applications, there are almost no studies oriented to study the impact of interventions using luminosity data in the LAC region and none in the transport sector. The only study in the LAC region that has used this data is Corral and Schling (2017) that applies synthetic control methods to show that shoreline stabilization investments have beneficial medium-term effects in economic growth in Barbados. Our aim with this work is not only to evaluate for the first time the impacts of road investments in Haiti and in LAC, but to showcase how non-traditional sources of data may be more widely used for impact evaluation in transport and in areas where access to information may be a limitation. We believe that this exercise could be usefully replicated in multiple countries, where transport investments are an important part of infrastructure investments and no evidence about its effectiveness is available.

From a methodological perspective, this paper also moves several steps further by carefully addressing multiple of the concerns related to unobserved heterogeneity. These concerns are central in the literature given the non-random placement of infrastructure investments (Yanez-Pagans et al., 2018). In particular, we run alternative specifications that rely on introducing multiple fixed effects. We test parallel-trend assumptions, present several placebo tests, and a series of robustness checks. In addition, although our preferred analysis is at the communal-section level, we also explore effects within one squared-kilometer areas (pixel level).[3] This allows for a better understanding of how localized or dispersed impacts can be. Moreover, by exploiting historical data for a period of more than ten years, our focus is both on short and medium-term effects, which is relevant for transport investments that usually may take some time to deliver effects. One the main limitations of previous transport evaluations that have used primary data is that they only cover two periods of time (baseline and follow-up) and cannot uncover dynamic effects or test model assumptions (Valdivia, 2011).

Our main result indicates that roads generate approximately between a 6% (considering the pre- and post-completion periods) and 26% (considering only the post-completion period) increase in night-time luminosity at the communal-section level. Taking into account the national level elasticity between luminosity values and GDP, we approximate that this type of transport interventions translate in communal section-GDP increases of at least 0.5% after investment approval, and possibly as high as 2.1%, after road rehabilitation completion. These average effects hide some important heterogeneity. First, communal sections that gain the most from these investments appear to be those in the middle of the income distribution, while we do not see any significant effects in the richest or poorest areas. Second, our results indicate that most impacts appear four or more years after project approval, at a similar level to the effects for investments completed during our analysis period. This makes clear that roads need to be fully operational before households and communities start realizing large benefits. Third, we find no evidence that those communities experiencing the largest gains in transport cost savings and accessibility (i.e. those that are further away from main cities) are necessarily those

[3]As is discussed below, there could be drawbacks to relying on pixel-level luminosity data, and this is why we consider pixel-level analyses only as additional useful information, but they are not our main focus.

attracting more economic activity. Finally, our pixel-level analysis suggests impacts are consistently concentrated in a buffer of 2 km in either side of the roads and drop off fairly quickly after that.

After this introduction, this paper is organized as follows. Section 2 discusses Haiti's national road network and the road improvement interventions analyzed. Section 3 discusses the data while section 4 presents the empirical strategy. Section 5 presents the results, including the preferred specification, robustness and placebo tests, heterogeneity and pixel-level analyses, and estimation of the relationship between luminosity and economic activity. Section 6 concludes.

2 Haiti's national road network and road improvement interventions

Haiti's national road network has a total length of 3,563 km, consisting of 905 km of primary roads (25%), 1,315 km of secondary roads (37%), and 1,343 km of tertiary roads (38%). This length reflects very low coverage levels for both the size of the population (0.4 km/1,000 inhabitants) and the surface area of the country (0.12 km/km^2). Moreover, the road network has poor infrastructure and maintenance conditions reflected in high transportation costs and travel time. An inventory taken in 2004 found that only 5% of the country's roads were in good condition and that since 1991 the country had actually lost more than 1,000 kilometers of rural roads due to lack of maintenance (BID, 2018).

Table 1 summarizes road improvement projects implemented in Haiti's national or primary road network between 2000 and 2013. This information was collected using on-line sources and archival project information since 1995 from three important donors in the country: the Inter-American Development Bank (IDB), the World Bank (WB), and the European Union (EU). Taking into account the specific location of each of these interventions, we were able to geo-reference them and merge this information with other geo-referenced information. As luminosity data, our main outcome variable, is only available until 2013, we concentrate on all projects approved prior to 2013. All of the projects included are rehabilitation works on already existing paved roads.[4] This means, all segments included in the analysis (treated or control) are paved but have different levels of maintenance conditions.

[4]For comparability purposes, we exclude from the analysis National Route 5 that was not paved

3 Data

We combine multiple sources of data, namely satellite imagery data, administrative data, and secondary data to produce a novel geo-referenced panel for Haiti. To measure impacts on economic activity we use information on remotely sensed night light density data from the Defense Meteorological Satellite Program, Operational Linescan System (DMSP/OLS) available from the National Oceanic and Atmospheric Administration (NOAA).[5] The available satellite-year data reports intensity of lights in grid that approximates to 0.86 km^2 near the equator, and it takes integer values from 0 to 63, zero meaning no light and 63 being the most intense. Each of these values is a composite constructed from many raw satellite images taken over the year and reflects average light intensity,[6] over all cloud-free dates. Data is available from 1992 to 2013, at annual intervals.

We conduct an archival analysis to construct a geo-referenced series of road improvement interventions that took place in the national road network. This exercise allows us to know the exact timing and location of each rehabilitation intervention between 1995 and 2013. To further characterize the areas of influence around road segments, we use two other sources of satellite imagery. The first one is the Normalized Difference Vegetation Index (NDVI), which is a measure of the greenness of the vegetation, and can allow us to capture changes in vegetation that may be correlated with land-use changes.[7] This is monthly data collected by NASA's Earth Observatory Group and is available from 2000 to 2013 at approximately 11.132 km^2 of resolution. The second source of data is monthly rainfall data from The Tropical Rainfall Measuring Mission (TRMM), a joint mission of NASA and the Japan Aerospace Exploration Agency. This data is available from 1998 to 2013 at approximately 27 km^2 resolution.[8]

Given the high incidence of natural disasters in the country and how they may affect luminosity levels, we use an on-line search engine of news to construct a geo-referenced panel on natural disaster occurrences across the country between 1995

[5] Available from https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html (February 2018).

[6] By considering the average light intensity through the year, our measurement of luminosity is capturing constant light over time. This light could come from residential and non-residential buildings, street lighting, constant traffic, and others. The key aspect is that the fact of it being constant may capture some aspects correlated to economic activity.

[7] Source: https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD_NDVI_M

[8] Source: https://neo.sci.gsfc.nasa.gov/view.php?datasetId=TRMM_3B43M

and 2013 (Table 2 presents this information). In addition, we geo-reference other infrastructure interventions that took place during the period of analysis and that could also affect our outcome variable, such as housing improvements, secondary roads rehabilitation, water, and energy-related projects implemented by the IDB or the WB (Table 3 presents this information). We also construct a geo-referenced panel using data from the 2003 population census and population projections for 2009 and 2015 from the Institut Haïtien de Statistique et d'Informatique. Finally, we use country-level GDP data from the World Development Indicators of the World Bank and micro-level data from the Demographic and Health Survey (DHS) from 2000, 2006, and 2012 to better understand the correlation between luminosity, GDP, and household wealth.

4 Empirical strategy

We estimate multiple difference-in-differences (DID) panel fixed effects models. To identify treated and control areas we construct 2.5 km buffers on each side of all road segments that belong to the national road network and exploit the differential timing of interventions as well as the fact that not all of the network received an intervention during the period of analysis. Our main unit of observation is the communal section, which is the minimum administrative unit of data collection in the country. There are a total of 570 communal sections in the country and a total of 213 intersecting the buffers of interest. Figure 1 depicts the roads that were never treated and those that were treated at any point in time during the period of analysis. The top panel shows with shading the luminosity levels in 2000, while the bottom panel shows the luminosity levels in 2013, the first and last observations in our panel.

We also run regressions using 0.86 km^2 pixels as our unit of observation. There are a total of 28,800 pixels in the country and 4,108 intersect the buffers. As we discuss below, results are consistent across both units of observation, but we prefer the communal section analysis as we believe it facilitates the economic interpretation of results. To compute the luminosity value at the a communal section level we add the luminosity values of all pixels that lie within its boundaries, regardless of whether pixels are inside or outside the buffers of influence. When we conduct the analysis at the pixel level, we only quantify changes in luminosity values of pixels that lie within the boundaries of the buffers of interest. Figure 2 presents the ever treated and never treated communal sections (top panel) and pixels (bottom panel) used in the analysis.

Our econometric specifications are all a version of the following baseline equation:

$$Y_{its} = \beta_0 + \beta_1 T_{it} + \beta_2 X_{it} + \beta_3 Z_{it-j} + \alpha_t + \lambda_i + \eta_s + \varepsilon_{its} \tag{1}$$

where, Y_{its} is the luminosity level for communal section (or pixel) i at time t (year) obtained by satellite s. T_{it} is the treatment indicator that takes the value of one starting in the year when the intervention is approved for the road segment (and accompanying buffer of influence) in that communal section (or pixel) and zero otherwise. X_{it} are contemporaneous time varying covariates that might affect the outcome: population, mean NDVI, total annual precipitation, and other infrastructure projects (listed in Table 3). We also explicitly include a dummy variable for areas affected by the 2010 earthquake, which takes the value of 0 for all years prior to 2010 and the value of 1 from 2010 onwards. Z_{it-j} introduces lags $1, ...j$ of total annual precipitation, mean NDVI, and natural disaster occurrences (those listed in Table 2). We use the Akaike information criterion (AIC) for model selection, to choose the optimal number of lags (it turns out to be one $j = 1$). To control for country-wide shocks, and for possible time-invariant unobservable characteristics at the communal section (pixel) level, we include year α_t and communal section (pixel) λ_i fixed effects. In some years two different satellites capture the information and provide different values for luminosity. This occurs because as technology improves luminosity data can be captured differently.[9] Usually (but not always), there are periods of overlap during the introduction phase of new satellites. To exploit all of the data available and avoid an ad-hoc combination or averaging of values within a year, we follow Gendron-Carrier et al. (2018) and pool data across all satellites, and include satellite fixed effects η_s to control for any differences in technology that may affect luminosity values. Finally, ε_{its} is the error term. Standard errors are clustered at the communal section level to account for potential contemporaneous (within communal section) and serial correlation. We estimate different versions of equation (1), by changing the size of the buffer of influence, using communal section or pixel data, or by running it for different sub-populations. In all cases, the parameter of interest is β_1. All else equal, a positive parameter estimate indicates that roads that receive the intervention exhibit larger increases in luminosity levels

[9]The satellite data relies on satellites F12 (1994-1999), F14 (1997-2003), F15 (2000-2007), F16 (2004-2009) and F18 (2010-2013), creating several years of overlapping information.

over time when compared to those that do not.

We also run other specifications where we replace $\beta_1 T_{it}$ with $\sum_{k=0}^{K} \delta_{-k} T_{it-k}$, where now T_{it-k} is a dummy equal to one if the approval of the intervention occurred k periods in the past, and zero otherwise. Thus the coefficients δ_{-k} represent the treatment effect of interventions approved k periods ago. This allows us to understand whether there are differential impacts over time. In the same way, in other specification we add the term $\sum_{k=1}^{Q} \delta_{+k} T_{it+k}$ where T_{it+k} is a dummy equal to one if the intervention will occur in k periods in the future, and thus δ_{+k} represents the anticipation effect of an intervention that will start in k periods. We expect this coefficient to be zero. This second specification allows testing a key identifying assumption when estimating DID models, the parallel trends assumption (Angrist and Pischke, 2009). Under a DID model it should not be a concern if treated and not treated units present differences in pre-treatment levels of the dependent variable, as long as they do not differ in the pre-treatment trends in that variable. For example, a concern could be that roads that received an intervention are those located in areas where economic activity is growing faster (or slower) when compared to control roads. This would generate a selection bias that would invalidate our identification strategy. An examination of Haiti's investment and development plans, as well as conversations with transport specialists involved in the country's development plans, suggest that there has not been an organized road improvement strategy in the country over the past decades. In fact, following project reports we do notice that some improvements seem to have followed the location of natural disasters and the need to rebuild those areas, bringing some sort exogenous variation to our treatment variable.

4.1 Transformations of night-light luminosity data

A well known problem of satellite luminosity data is that the imagery suffers from blurring, or overglow of the lit areas. That is, light emitted in some areas, such as cities, often falls outside their respective boundaries, which magnifies their true size (Imhoff et al., 1997; Henderson et al., 2003). Regarding this issue, Abrahams et al. (2016) argue that blurring occurs due to the on-board optics of satellites, because the sensor scans the earth's surface in elliptical areas, but ascribes the observed light to smaller, square-shaped pixels. To understand how overglow is generated, the authors rely on detailed information about the satellite's altitude, the radius of its optics, and its location above the Earth's surface on any given night to recreate the geometry of the satellite's data collection process and ultimately remove all overglow effects from the luminosity data (Corral and Schling, 2017). They develop a deblurring methodology, which is a partially statistical algorithm that corrects this bias to obtain a more appropriate approximation of true luminosity values. They are able to show that the method is successful at more accurately estimating the extent of city boundaries in the case of over 11 sub-Saharan African and South Asian cities. We apply this same deblurring methodology and report estimation results both with raw and deblurred measures of luminosity.

Another issue we encounter is that a substantial fraction of the pixels in our data set appear with a zero level of luminosity. This occurs because the area of study (i.e. Haiti) has an sparse population without access to electricity and thus the satellite sensor cannot capture the light. As mentioned before, it is important to keep in mind that our measures of luminosity is a composite constructed from many raw satellite images taken over the year and reflects average light intensity. This means that what we observe is the capture of light that is constant over time. Sources generating this light might be diverse. They could come from residential and non-residential buildings, street lighting, constant traffic, and others. The key aspect is that observing this constantly implies there are aspects in that particular geographic space that indicate the existence of sufficient economic activity. In order to be able to use an specification equivalent to the logarithm of the light density as our outcome variable, and given the large number of zeros, we apply the inverse hyperbolic sine transformation (IHS) to the average luminosity value of the communal section or pixel. Therefore, our outcome variable is defined as $Y_i = \log(y_i + \sqrt{y_i^2 + 1})$, where Y_i is the raw or deblurred luminosity of the communal section or pixel i.[10] The IHS transformation is defined at zero, and the interpretation of the coefficients using it is equivalent to that of logarithms.

As mentioned above, another aspect of DMSP/OLS luminosity data is that it is upper bounded at a value of 63. This can have implications in terms of adequately capturing impacts in areas that are densely populated and where luminosity values have already reached the ceiling. To overcome this issue, in some of our econometric estimations we use an alternative luminosity variable, Global Radiance Calibrated (GRC), also provided by NOAA. This data is captured when the satellite sensor was set to be less sensitive, and therefore not upper-bounded.

[10] See Pence (2006).

This information, however, is only available for cross-sections years 1995, 2000, 2005 and 2010. GRC data are less ready to recognize dim light sources, yet can quantify variety in light inside locales that are top-coded in the DMSP/OLS version (Gonzalez-Navarro and Turner, 2016).[11]

5 Results

5.1 Baseline descriptive statistics

Table 4 presents summary statistics for the communal sections in the sample. We divide them in two groups. The first is composed by those communal sections that were never treated during the study period, this means none of the buffers of road segments that received a rehabilitation project touch the boundaries of these communal sections. The second are those communal sections that received a road improvement intervention at any given year within the time frame of the analysis. We can see that there are no significant differences across some of the variables, such as the greenness of the vegetation (NDVI) or the number of other types of projects (energy, roads, housing, etc.) that they received. There are however, some differences worth pointing out. Ever treated communal sections have smaller populations and are exposed to more rainfall. As mentioned above, the implementation of a DID method does not require equality in variable levels at baseline, but parallel trends. We conduct tests to show that this is the case. It should be noted that the deblurring process removes the upper bound of the raw DMSP/OLS data.

5.2 Main effects and interpretation

Table 5 presents, step by step, how we arrive to our preferred specification. Using the IHS of deblurred luminosity at the communal section level (with a 2.5 km buffer of influence) as the dependent variable, columns (1) to (4) gradually introduce multiple fixed effects in the model. Without covariates or fixed effects (column 1), the magnitude of the coefficient of interest is 0.201, which means that, on average, a communal section that received a road improvement intervention sees

[11] See Ziskin et al. (2010) for an explanation of the underlying methodology.

an increase of 22.3% in its luminosity levels[12]. Introducing only communal section fixed effects (column 2) makes the effect even stronger to almost 35%, but introducing year fixed effects (column 3) or both year and satellite fixed effects (column 4) reduces the impacts to 11%. In column (5) we include contemporaneous time-varying controls considering other infrastructure projects implemented in the country that could also affect the luminosity values recorded. More specifically, we control for energy projects, other road improvement projects in the secondary or tertiary network, housing and urban development projects[13]. We also control for population, natural disasters occurrence and a dummy variable for areas affected by the 2010 earthquake. In column (6) we include not only the contemporaneous effects but also one lag for annual levels of precipitation, NDVI, and natural disaster occurrence. As mentioned above, the AIC indicates that one lag is the optimal lag specification. Even though there are no large differences between columns (5) and (6), our preferred specification is presented in column (6) where we include the complete set of covariates and where impacts are around 7%.[14]

As discussed above, we use deblurred luminosity to account for potential measurement error in luminosity levels. However, in Table 6 we explore alternative measures of luminosity and see how they might affect the obtained results. In column (1) we replicate the regression in column (6) from Table 5, which is our preferred specification using deblurred luminosity. In columns (2) and (3) we estimate the same specification using two alternative measures of luminosity. In column (2) we use the IHS of the DMSP-OLS raw luminosity value, as provided by NOAA. Using this variable we find an even larger effect of 11%. In column (3) we use the GRC measure that is not upper-bounded. This alternative measure of luminosity suggests that the impact of road interventions are in the order of 15%. The fact that

[12]When regression models have log transformed outcomes the impact of a one-unit change in a covariate (X) is calculated by exponentiating the coefficient. In this case it will be $(exp(\beta_1) - 1) = exp(0.201) - 1 = 0.223$. When the estimated coefficient is less than 0.10 the interpretation that a unit increase in X is associated with an average of $100 * \beta_1$ percent increase in Y works well. We refer to the exponetiated coefficients throughout the text, unless we specify otherwise)

[13]The list or number of other projects included is limited to IDB and World Bank projects, given that it was constructed based on publicly available information. If it were to be the case that there are control areas projects for which we do not have information, this would create a downward bias, making our results conservative estimates of the road improvement projects impacts.

[14]Given that we are (implicitly) averaging observations in years where have two satellites reporting data, as an additional robustness check, we run regressions including only the luminosity values of the newest satellite each year, while still keeping the satellite fixed effects to capture the changes in technology. Results are consistent and the preferred model (column 6 in Table 5) shows an average impact of 8%.

this last result is larger than the one obtained in our preferred specification might be telling us that there are also gains in economic activity in urbanized and highly dense areas that are not being accounted for by the bounded measure.

5.3 Robustness and placebo tests

Table 7 presents several robustness checks. Column (1) shows again our preferred specification from column (6) of Table 5, which is based on a buffer of influence of 2.5 km at each side of the road. In columns (2) and (3) we report results obtained when changing the buffer to 3.5 and 5 km to each side of the road, respectively. These changes have a direct effect on the communal sections that are selected in the sample, as shown in the last line of the Table 7, where we can see the gains in sample size. Despite these changes, results remain close to our preferred specification, between the 6-7% range. In columns (4) to (6) of Table 7 we explore the robustness of the results to eliminating the largest populated areas. As some of the treated road segments serve to connect some larger cities, such as Port-au-Prince and Cap-Haïtien, we want to rule out the possibility that the luminosity gains that we observe are concentrated in those urban areas or are the result of agglomeration. For this, we exclude all those communal sections that are part of Port-au-Prince (column 4) or Cap-Haïtien (column 5), or both (column 6). Results remain stable in (4) and are equal to 7% and have just a marginal decrease in (5) and (6) to 6%.

As discussed above, a key identification assumption of the DID regressions is that the treated and control areas do not exhibit differences in *trends* before the interventions. We test this parallel trends assumption in two ways, as shown in Table 8. In column (1) we add a dummy variable identifying those communal sections that will be treated in the future, prior to approval. The coefficient on that dummy variable is not statistically significant, and the treatment effect post-approval of a project goes up to 12%. In column (2) we split the pre-treatment dummy in sub-periods prior to approval of a project (one, two, three, and four or more years prior to approval). None of those coefficients are significant, as expected, and a Wald test of joint significance of all four coefficients is not significant either. The treatment effect in this case is also equal to 12%.

Columns (3) and (4) of Table 8 present alternative tests of our identification strategy. In particular, we construct two placebo treatments, for which we do not expect to find a significant treatment effect. In column (3) we take luminosity values from 1992 to 1999 and use them to replace the actual luminosity values observed from 2006 to 2013. As we do not have enough historic information to replace 2004 and 2005 luminosity values (the first two years for which there is a treatment), we drop those two years from the regressions. We should not expect to see any impact of treatment when using those lagged years as output variables, and indeed the coefficient is close to zero and not statistically significant. We also conduct tests (not reported here[15]) replacing the values of other years with the historic data, for example, replacing values between 2004 and 2011 and dropping 2012 and 2013. In all cases the coefficient is close to zero and not statistically significant. In column (4) we create a different placebo treatment, this time randomizing the timing of the treatment (prior to actual road construction), and repeating this exercise for 200 replications. Here again, as expected, the results show there is no treatment effect.

5.4 Heterogeneous treatment effects

We test for heterogeneous treatment effects to further understand how impacts are distributed across space and time. Exploiting data from Haiti's Poverty Map from 2003 and looking at the distribution of the measure of Unsatisfied Basic Needs (UBN) across communal sections reported in this source, columns (1), (2), and (3) in Table 9 divide communal sections in three groups: poorest, poor, and least poor.[16] We observe that impacts are coming from communities in the middle part of the distribution (15% effect), which indicates that while the richest communities are not benefiting from these road improvement projects, the poorest of the poor are not gaining either. A test of equality of coefficients across groups, confirms that this difference is significant. This finding highlights the need to provide complementary policies in other areas (e.g. education, health, poverty reduction programs) to support those in the base of the pyramid, and that could allow them to take full advantage of the improvement in accessibility and transport connectivity.

In columns (4) and (5) of Table 9 we test whether distance to the main cities (i.e. Port-Au-Prince or Cap-Haïtien) has any role in explaining the impacts observed.

[15] Results can be requested from the authors.

[16] MPCE (2004) classifies the population according to their level of access to basic social services. Based on the official classification of the UBN, the poorest population corresponds to very weak and extremely weak, poor is the population with low access, and least poor corresponds to less weak and moderately weak.

One hypothesis, based on the notion of agglomeration effects, is that those communal sections that are closer to main urban areas might be the ones that exhibit the largest growth in economic activity (i.e. luminosity values). As opposed, if impacts are driven by transport costs savings and gains in accessibility, one would expect that those communal sections further away should be experiencing higher impacts. Results seem to indicate that there are no differences in impacts across distance. Although the estimated coefficient for communal sections that are further away is statistically significant and the one for those that are closer is not, the magnitudes are very similar and not statistically different. Variations in statistical significance across coefficients seems more related to lack of statistical power in the case of communal sections that are closer to the cities.

Finally, in columns (6) and (7) of Table 9 we test whether there are heterogeneous impacts at different years after project approval. This serves to test what the short, medium and long run effects of these investments are. In column (6) we interact the treatment dummy with number of years since project approval. We can see that most impacts appear after 4 or more years after project approval and the estimated impact during this period is close to 25%. This finding seems reasonable to the extent that households and communities might not experience any gains during construction, but can only get the benefits once the improved road is fully operational. We further test this hypothesis in column (7) by dividing the treatment variable in two periods, construction and after completion. Results show that impacts during construction are marginally significant and smaller (6%)than those that appear after completion (26%). The fact that our average effect is closer in magnitude to the impact computed here during the construction phase is due to observing only a few projects after completion in our sample as shown in Table 1.

5.5 Pixel-level results

In all the analyses so far we have relied on luminosity values aggregated at the communal section level. We have done this as we believe it is the more appropriate unit of measure to provide an economic interpretation of the results. However, we also estimate the model using pixel-level data. We do not see this exercise as a way to estimate changes in economic activity at the pixel level, since nightlights might not be appropriate proxies for GDP for very small areas. Rather, the analysis gives us as a way to explore whether luminosity impacts are concentrated only around the intervened roads or not, and how far away from the roads the impacts might materialize.

Table 10 serves as way to establish the comparability of the prior communal section results and the pixel ones, for different specifications of the buffer of influence (columns 1 to 3), eliminating the pixels associated to Port-au-Prince (column 4), Cap-Haïtien (column 5), or both (column 6), and finally utilizing the GRC measure of luminosity (column 7). The pixel-level effects appear smaller than the communal section-level ones, in the order of 6%. Column (7) meanwhile, suggests large effects (17%) when using the GRC luminosity measure, which is in line with the results in Table 6 which also showed much higher effects using the GRC luminosity measure[17].

Table 11 exploits the pixel-level regressions to explore heterogeneous treatment effects across different buffers of distance. As mentioned before, this is the central objective of this section and allows to have some evidence on whether there isa gradient of impacts by distance to the intervened road. For each definition of the buffer of influence, three regressions are run: the first one only uses pixels within less than a 1 km from the road, the second uses only pixels between 1 and 2 km from the road, and the third one uses pixels above 2 km, and up to the boundary of the buffer of influence (2.5, 3.5 or 5 km). The results show that treatment effects on pixels within 1 km of the road are around 11%, those for pixels between 1 and 2 km are smaller but still significant, between 7% for the 2.5 km buffer to 10% for the 5 km buffer. Finally, the treatment effects pretty much disappear after 2 km (they are only significant at the 10% level for the 5 km buffer). This suggests that the effects may be even larger than those estimated using communal section level data, but that they drop off fairly quickly, being concentrated in a buffer of 2 km in either side of the roads.

5.6 Night-light luminosity data as a proxy for economic activity

An important assumption in this analysis is that the outcome variable (luminosity values) is a good proxy for economic activity and development. To empirically test this assumption, we use national level data and compute the elasticity between the

[17] The fact that the estimated coefficient with the GRC measure is larger than the one estimated with the upper-bounded measure reflects the fact that the GRC data source, by combining very small values with unbounded values, is reducing the weight or ignoring really small values while also highlighting or putting more weight on larger values that were previously not available.

luminosity value and the Gross Domestic Product (GDP). Table 12 reports these elasticities for both the raw luminosity values and the deblurred luminosity. We start with the most basic specification, without including any controls, and obtain elasticities between 0.06 and 0.07 for raw and deblurred luminosity, respectively. We then start adding satellite fixed effects to take into account changes in technology that might affect the values reported within a given year and a fixed-effect for the 2010 earthquake. In the most complete specification, reported in columns (3) and (6), we obtained elasticities of 0.06 and 0.08 for raw and deblurred luminosity, respectively.

One of the most challenging aspects of working with luminosity data is the economic interpretation of results. To provide a first approximation, we take into account that the national level elasticity we estimate for the deblurred luminosity values and GDP is around 0.08. If we assume that this elasticity also holds at the communal-section level, and considering that the impact or receiving a road improvement intervention on luminosity values that we consistently estimate lies within 6% and 26% (for the communal section regressions), this would imply that road investments could have generated between 0.5% and 2.1% increase in the communal-section GDP in Haiti.

We also exploit household-level data from the Demographic and Health Survey (DHS) to compute the elasticity between the average household asset index and the luminosity values computed at the communal section level. Results are reported in Table 13. Column (1) shows that a one percent increase in luminosity at the communal section i is associated with a two percent increase in the average asset index (DHS_a) of the communal section. Column (2) includes fixed effects at the communal section level. This specification obtains an elasticity of 0.05. We also include year (column 3) and satellite (column 4) fixed effects, and the elasticities are around 0.02. By combining these results with the estimated impacts, we suggest that receiving a road intervention could lead to an increase of 0.1% and 0.5% in the average household asset index at the communal section level.

6 Conclusion

We provide novel evidence on the impacts that transport investments have had in promoting economic activity, proxied by satellite luminosity data, in Haiti. Given the lack of information and fragile conditions in the country, there are still very few causal studies providing empirical evidence on the impacts generated by the large package of financial assistance that the country has received in the past years, particularly since the 2010 earthquake. Beyond the contributions to the discussion around the effectiveness of financial aid in Haiti, this is also the first study providing evidence on the impacts of transport infrastructure investments using satellite data in Latin America and the Caribbean and constitutes also one of the very few causal analysis on this topic.

As it was shown throughout the study, from a methodological perspective, this paper also moves several steps further in the literature by carefully addressing multiple of the concerns related to unobserved heterogeneity. These concerns are key in the related literature given the non-random placement of infrastructure investments and the inherent identification challenges that this brings. The results we consistently obtain across multiple specifications indicate that a road rehabilitation project leads to an increase in luminosity values between 6% and 26% at the communal section level (the preferred level of analysis for an economic interpretation of results). Taking into account the national level elasticity between luminosity and GDP, we approximate that transport investments have generated between 0.5% and 2.1% increase in the communal-section GDP of the intervened communal sections, during the period of analysis.

The average effects we observe hide some important heterogeneity. First, communal sections that gain the most from these investments are those in the middle of the distribution of an Unsatisfied Basic Needs indicator, while we do not see any significant effects in the richest or poorest areas according to this same metric. This implies that in order to tackle poverty reduction and promote inclusive growth in the country, transport investments will not be impactful entirely by themselves, but rather there is need for complementary policies across different sectors (e.g. education, health, poverty reduction programs) to support and lift those in the base of the pyramid. Second, our results indicate that most impacts appear four or more years after project approval. This is consistent with the notion that roads need to be fully operational before households and communities start seeing any benefits. The full or more longer term impacts are actually much larger and could be close to a 26% increase in luminosity values (i.e. 2.1% increase in GDP). Third, we find no evidence that those communities experiencing the largest gains in transport cost savings and accessibility are necessarily those attracting more economic activity. This is reflected in the fact that regardless of the distance to the main cities, effects remain constant. Finally, our pixel-level analysis suggest that impacts are consistently concentrated in a buffer of 2 km on either side of the intervened roads, and drop off fairly quickly after that.

The context of Haiti is quite unique, given the high levels of poverty in the country and the sizable natural disasters experienced over the past years, particularly the 2010 earthquake. Our empirical strategy explicitly controls for all natural disasters and specifically for the 2010 earthquake. In addition, robustness checks excluding large cities that were affected by the earthquake, such as Port Au Prince, still provide similar conclusions. Thus, we believe our results are not contaminated or just capturing the effects of the earthquake recovery effort. Nevertheless, it is still possible that the large and positive impacts observed in this case might not necessarily occur in other (more developed) settings. Future research replicating this approach for other countries might provide useful insights on the heterogeneity of effects across areas with different institutional and socioeconomic characteristics, and baseline development levels. It is reasonable to expect that the economic multipliers of infrastructure investments are larger in contexts with higher levels of poverty and lower development level.

Moving forward, this work opens multiple avenues or opportunities for evaluation research. The methodological approach we propose in this study can be useful for public agencies, international organizations, and other institutions seeking to evaluate the impacts of transport investments, particularly in settings where data availability may be limited. Important challenges still remain and have to do with the appropriate economic interpretation of these results, and a better understanding of what nigh-time lights are really measuring. The literature has done some progress along these lines recently (Machemedze et al., 2017; Chen and Nordhaus, 2011; Klemens et al., 2015), but in contexts with limited other data available, these correlations will still need to be taken as given.

References

Abrahams, A., Lozano-Gracia, N., and Oram, C. (2016). Deblurring DMSP Nighttime Lights. Technical report, Working Paper.

Alder, S. (2017). Chinese Roads in India: The Effect of Transport Infrastructure on Economic Development. University of North Carolina at Chapel Hill.

Alix-Garcia, J. M., Sims, K. R., and Yañez-Pagans, P. (2015). Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's Payments for Ecosystem Services Program. *American Economic Journal: Economic Policy*, 7(4):1–40.

Angrist, J. and Pischke, J. (2009). Mostly Harmless Econometrics. An Empiricist's Companion. Princeton University Press.

Banerjee, A., Kumar, S., and Pande, R. (2012). Connectivity and Rural Development: Examining India's Rural Road Building Scheme.

BID (2018). Haiti invests heavility in rebuilding roads. https://www.iadb.org/en/news/webstories/2009-04-13/haiti-invests-heavily-in-rebuilding-roads%2C5339.html. Web Stories. Accessed July 10, 2018.

Casaburi, L., Glennerster, R., and Suri, T. (2013). Rural roads and intermediated trade: Regression discontinuity evidence from Sierra Leone.

Cavallo, E., Powell, A., and Becerra, O. (2010). Estimating the direct economic damages of the earthquake in haiti. *The Economic Journal*, 120(546):F298–F312.

CBS (2010). Red cross: 3m haitians affected by quake. https://www.cbsnews.com/news/red-cross-3m-haitians-affected-by-quake/. Accessed June 8, 2018.

CEPR (2012). Center for Economic and Policy Research. Lack of Data Prevents Measurement of Aid Effectiveness, Impact. http://cepr.net/blogs/haiti-relief-and-reconstruction-watch/lack-of-data-prevents-measurement-of-aid-effectiveness-impact. Accessed June 5, 2017.

Chandra, A. and Thompson, E. (2000). Does public infrastructure affect economic activity? Evidence from the rural interstate highway system. *Regional Science and Urban Economics*, 30(4):457–490.

Chen, X. and Nordhaus, W. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Science (PNAS)*, 108(21):8589–8594.

Corral, L. and Schling, M. (2017). The impact of shoreline stabilization on economic growth in small island developing states. *Journal of Environmental Economics and Management*, 86:210 – 228. Special issue on environmental economics in developing countries.

Datta, S. (2012). The impact of improved highways on Indian firms. *Journal of Development Economics*, 99:46–57.

Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., and M.A., T. (2018). Subways and urban air pollution. *NBER Working Paper*, (24183).

Gertler, P., Gonzalez-Navarro, M., Gracner, T., and Rothenberg, A. (2014). The Effects of Road Quality on Household Welfare: Evidence from Indonesia's Highways. *Working Paper*.

Ghani, E., Goswami, A. G., and Kerr, W. R. (2016). Highway to Success: The Impact of the Golden Quadrilateral Project for the Location and Performance of Indian Manufacturing. *The Economic Journal*, 126(591):317–357.

Gonzalez-Navarro, M. and Quintana-Domeque, C. (2016). Paving streets for the poor: Experimental analysis of infrastructure effects. *Review of Economics and Statistics*, 98(2):254–267.

Gonzalez-Navarro, M. and Turner, M. A. (2016). Subways and urban growth: evidence from earth.

Henderson, J., Storeygard, A., and Weil, D. (2012). Measuring economic growth from outer space. *The American Economic Review*, 102(2):994–1028.

Henderson, M., Yeh, E. T., Gong, P., Elvidge, C., and Baugh, K. (2003). Validation of urban boundaries derived from global night-time satellite imagery. *International Journal of Remote Sensing*, 24(3):595–609.

IDB (2017). Haiti IDB Group country strategy 2017-2021. http://idbdocs.iadb.org/wsdocs/getdocument.aspx?docnum=EZSHARE-1232983971-18. Accessed December 6, 2018.

Imhoff, M., Lawrence, W., Stutzer, D., and Elvidge, C. (1997). A technique for using composite DMSP/OLS City Lights satellite data to map urban area. *Remote Sensing of Environment*, 61(3):361 – 370.

IPA (2016). Innovations for Poverty Action. Micro-satellite Data: Measuring Impact from Space. Joint with CEGS.

Khanna, G. (2016). Road Oft Taken: The Route to Spatial Development. University of Michigan.

Klemens, B., Coppola, A., and Shron, M. (2015). Estimating local poverty measures using satellite images. a pilot application to central america. Policy Research Working Paper 7329. World Bank Group.

Machemedze, T., Dinkelman, T., Collinson, M., W., T., and M., W. (2017). Throwing light on rural development: using nightlight data to map rural electrification in sputh africa. DataFirst Technical Papers No. 38.

MPCE (2004). Carte de Pauvrete d'Haiti. Technical report, Ministere de la Planification et de la Cooperation Externe. Republique d'Haiti.

Pence, K. M. (2006). The role of wealth transformations: An application to estimating the effect of tax incentives on saving. *The BE Journal of Economic Analysis & Policy*, 5(1).

Storeygard, A. (2016). Farther on down the Road: Transport Costs, Trade and Urban Growth in Sub-Saharan Africa. *Review of Economic Studies*, 83:1263–1295.

The World Bank (2012). Poverty headcount ratio at national poverty lines (% of population). Global Poverty Working Group. Accessed June 5, 2017.

The World Bank (2018). Haiti GDP Data: World Bank national account data and OECD national accounts data files. https://data.worldbank.org/country/haiti. Accessed June 8, 2018.

UNDP (2013). United Nations Development Program. Report Millenium Development Goals 2013: Haiti a new look. Accessed June 5, 2017.

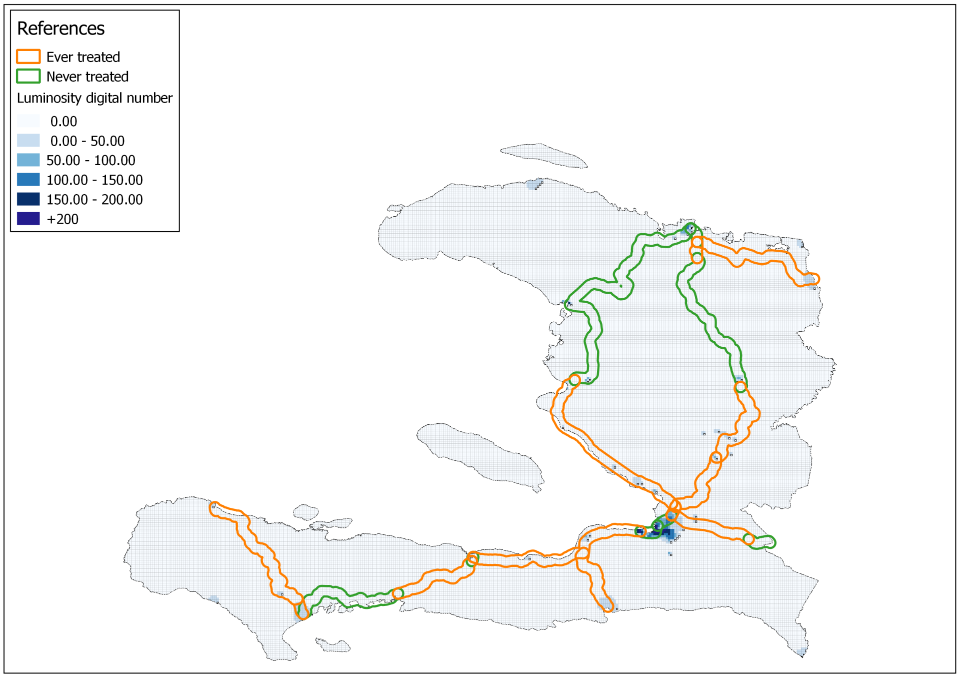
U.S. Congress (2014). S.1104, 113th congress - Assessing Progress in Haiti Act of 2014. https://www.congress.gov/bill/113th-congress/senate-bill/1104?r=86. Accessed December 6, 2018.

Valdivia, M. (2011). Contracting the road to development: Early impacts of a rural roads program. PEP Working Paper serie No. 2010–18.

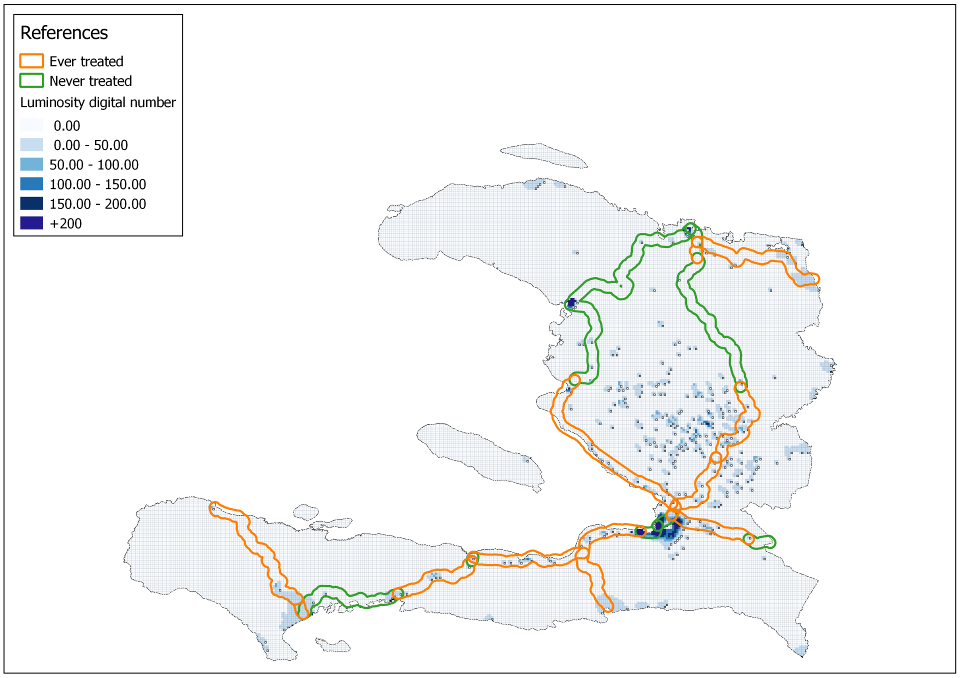
van de Walle, D. and Cratty, D. (2002). Impact evaluation of a rural road rehabilitation project. Working Paper 44472, Washington, DC: World Bank.

Yanez-Pagans, P., Martinez, D., Mitnik, O., Scholl, L., and Vasquez, A. (2018). Urban transport systems in latin america and the caribbean: Lessons and challenges. Technical Note No. 01518. Office of Strategic Planning and Development Effectiveness, Transport Division, IDB Invest. Inter-American Development Bank Group.

Ziskin, D., Baugh, K., Hsu, F.-C., and Elvidge, C. D. (2010). Methods used for the 2006 radiance lights. *Proceedings of the Asia-Pacific Advanced Network*, 30:131–142.



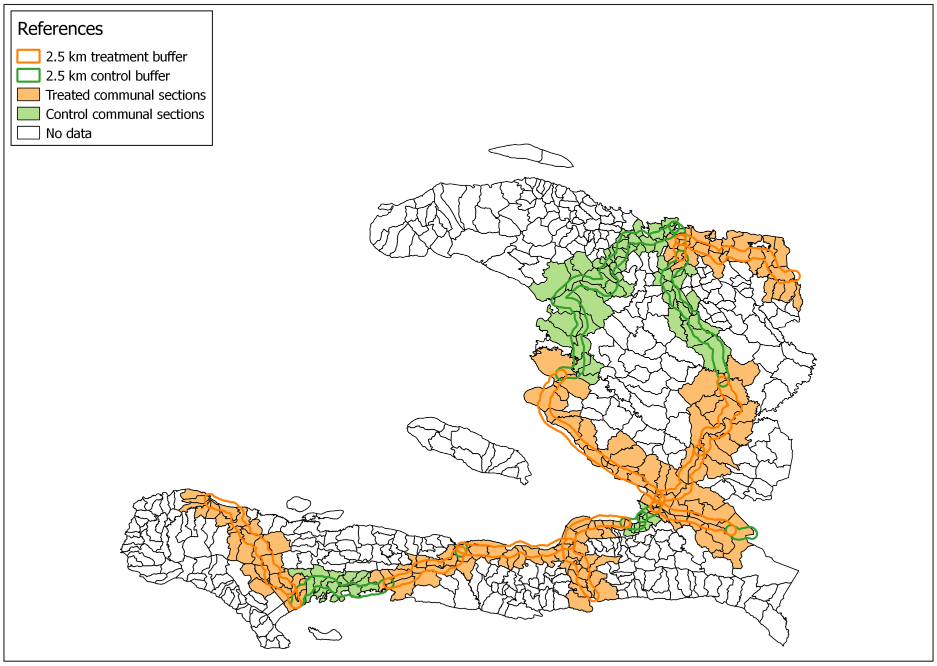
(a) Year 2000



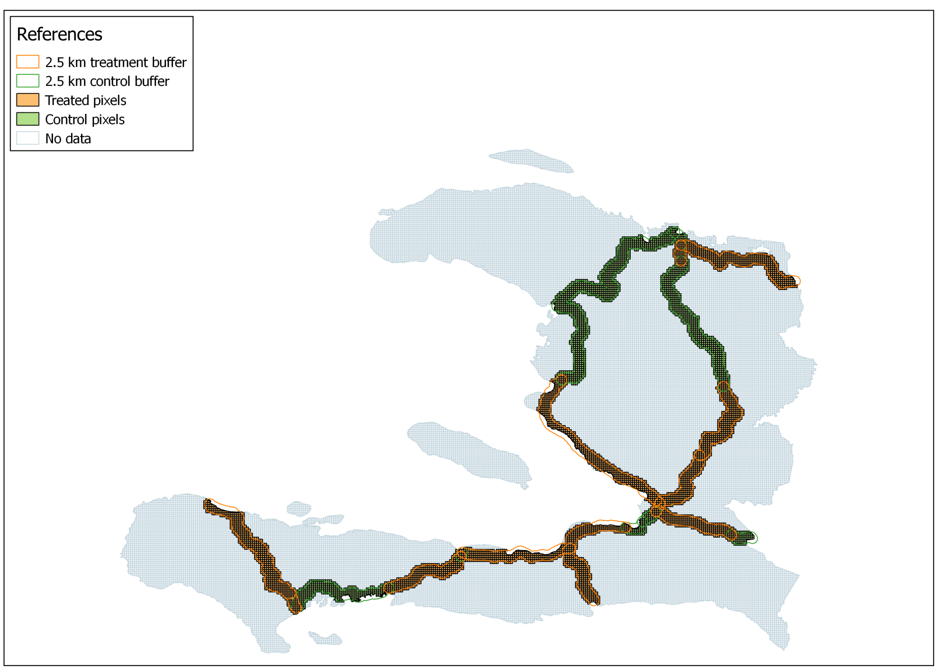
(b) Year 2013

Data for year 2000 is taken from satellite F15, while for year 2013 is taken from satellite F18.

Figure 1: Deblurred luminosity



(a) Communal sections



(b) Pixels

Figure 2: Unit of observation

Table 1: Rehabilitation projects approved for the national road network between 2000 and 2013

Financing institution	**Road**	**Section**	**Year approved**	**Year finished**	**Amount (in US$ M)**	**Length (in km)**
IDB_1	RN1	Carrefour Shadá - St. Marc	2005	2013	77.8	94.3
IDB_2	RN7	Les Cayes - Camp Perrin	2007	2013	100	15.0
		Camp Perrin - Beaumont				33.0
		Beaumont - Roseaux				26.0
		Roseaux - Jérémie				18.0
IDB_3	RN1	Bon Repos - Titanyen	2010	2013	29	14.5
		Titanyen - Xaragua				49.0
		Xaragua - St. Marc				22.2
	RN2	Fond de Negres - Aquin	2010	2013	29	22.7
		Miragoâne - Fond des Negres				25.7
IDB_4	RN7	RN7	2011	2015	55	100.0
	RN8	Crx d. Bouquets - Fond Parisien				37.0
EU_1	RN3	Port-au-Prince - Mirebalais	2005	2010	35.4	42.1
EU_2	RN3	Mirebalais - Hinche	2005	2011	34.5	53.8
EU_3	RN6	Cap-Haïtien - Ouanaminthe	2004	2009	37	65.6

Continued on next page

Table 1 – *Continued from previous page*

Financing institution	**Road**	**Section**	**Year approved**	**Year finished**	**Amount (in US$ M)**	**Length (in km)**
WB_1	RN3	Barriere Battant - Carrefour la Mort	2006	2013	16	8.0
WB_2	RN2	Carrefour - Miragoâne	2010	2017	65	86.1
	RN4	Carrefour Dufort - Jacmel				44.6

Financing institutions:

Inter American Development Bank (IDB): IDB_1 (HA0087); IDB_2 (1922/GR-HA); IDB_3 (HA-L1046); IDB_4 (HA-L1054).

The European Union (EU): EU_1 (FED/2005/017-548); EU_2 (FED/2005/017-548); EU_3 (unknown).

The World bank (WB): WB_1 (P095523); WB_2 (P120895).

Table 2: List of natural disasters

Year	Description	Location
1998	09/23, Hurricane Georges	Sud-Est and Nord-Ouest
2002	05/24-05/27, tropical storms and flooding	Camp Perrin, L'Asile, Anse-à-Veau.
2004	05/23–05/24, torrential rains	Mapou, Belle-Anse, Bodary, and Fonds-Verrettes: Sud-Est département.
	09/10, Hurricane Ivan	Southern peninsula and west coast.
	09/18-09/19, Hurricane Jeanne	Artibonite. Gonaïves.
2005	07/06-07/07, Hurricane Dennis	Bainet, Grand-Goâve, Les Cayes.
	10/04, floods	Pétion-Ville and Grand-Goâve in the Ouest département.
	10/17–10/18, Hurricane Wilma	West and South of Haiti.
	10/23, tropical Storm Alpha	Grand'Anse and Nippes.
	10/25, flooding.	Port-de-Paix, Bassin-Bleu, Anse-à-Foleur.
2006	11/22-11/23, heavy rain	Grand'Anse Department and the Nippes and Nord-Ouest départements.
2007	03/17, floods.	Grand'Anse, Jérémie, Abricots, Bonbon, Les Irois

Continued on next page

Table 2 – *Continued from previous page*

Year	Description	Location
		Sud-Est: Jacmel, Ouest, Cité Soleil, Delmas, Port-au-Prince (Carrefour-Feuilles, Canapé Vert) Nord-Ouest:, Port-de-Paix, Saint-Louis du Nord, Anse-à-Foleur, Cap-Haïtien, Nord-Est: Ferrier, Ouanaminthe.
	05/08-05/09, torrential rain	Nord, Nord-Est and Sud départements.
2008	08/26, Hurricane Gustav	Sud and Grand'Anse départements.
	09/01, Hurricane Hanna	Artibonite and Nord-Est départements.
	09/06, Hurricane Ike	Nord, Ouest and Nord-Ouest départements.
2009	10/20, heavy rain	Carrefour.
2010	01/12, earthquake of magnitude 7.0	Port-au-Prince.
	01/20, a second earthquake of magnitude 6.1	Port-au-Prince.
	11/05, Hurricane Tomas	South-west.
2016	10/03-10/04, Hurricane Matthew	southwestern Haiti near Les Anglais.

Table 3: List of other infrastructure projects

Sector	**Financing institution**	**Description**	**Year approved**	**Amount (in US$ M)**
Energy				
	IDB$_5$	Péligre Hydroelectric Plant Rehabilitation Program	2008	12.5
	IDB$_6$	Rehabilitation of Electricity Distr. System in Port-au-Prince	2010	15.7
	IDB$_7$	Rehabilitation of Electricity Distr. System in Port-au-Prince, Phase II	2010	14
	IDB$_8$	Supplementary Financing for the Peligre Hydroelectric Plant	2011	20
	IDB$_9$	Rehabilitation of the Péligre Transmission Line	2014	7.7
Urban development	IDB$_{10}$	Urban Rehabilitation Program	2005	50
	IDB$_{11}$	Support to the Shelter Sector Response Plan	2010	30
	IDB$_{12}$	Infrastructure Program	2011	55
	IDB$_{13}$	Productive Infrastructure Program	2012	50
	IDB$_{14}$	Productive Infrastructure Program II	2013	40.5
	IDB$_{15}$	Water Management Program in the Artibonite Basin	2013	25
	IDB$_{16}$	Productive Infrastructure Program III	2014	55
	IDB$_{17}$	Sustainable Coastal Tourism Program	2014	36
	IDB$_{18}$	Productive Infrastructure Program IV	2015	41
	WB$_3$	Rural Community Driven Development - Additional Financing II	2010	15

Continued on next page

Table 3 – *Continued from previous page*

Sector	Financing institution	Description	Year approved	Amount (in US$ M)
	WB_4	Urban Community Driven Development Project	2011	30
	WB_5	Port-au-Prince Neighborhood Housing Reconstruction	2011	65
Other transport	IDB_{19}	Pont-Sonde - Mirebalais Highways and Access Roads	1990	53
	IDB_{20}	Support for Transport Sector in Haiti II	2012	53
	IDB_{21}	Emergency Road Rehabilitation Program in Response to Hurricane Sandy	2012	17.5
	WB_6	AF Infrastructure & Institutions Emergency Recovery	2012	35

Financing institutions:

Inter American Development Bank (IDB): IDB_5 (HA-L1032); IDB_6 (HA-L1014); IDB_7 (HA-L1035); IDB_8 (HA-L1038); IDB_9 (HA-L1100); IDB_{10} (HA-L1002); IDB_{11} (HA-L1048); IDB_{12} (HA-L1055); IDB_{13} (HA-L1076); IDB_{14} (HA-L1081); IDB_{15} (HA-L1087); IDB_{16} (HA-L1091); IDB_{17} (HA-L1095); IDB_{18} (HA-L1101); IDB_{19} (HA0049); IDB_{20} (HA-L1058); IDB_{21} (HA-L1086).

The World bank (WB): WB_3 (P118139); WB_4 (P106699); WB_5 (P125805); WB_6 (P130749).

Table 4: Communal section covariates, averages of years 2000-2003

Variable	Never treated		Ever treated		p-value
	Mean	Std. Dev.	Mean	Std. Dev.	difference
Deblurred luminosity	104.36	339.06	49.08	147.58	0.01
IHS of deblurred luminosty	0.59	1.47	0.49	0.99	0.20
Normalized Difference Vegetation Index (NDVI)					
Average index$_t$	0.66	0.16	0.63	0.15	0.01
Total rainfall (in MM, 1000)					
Total rainfall$_t$	8.23	7.86	10.71	7.37	0.00
Population (1000 hab.)	36.05	66.99	18.77	24.06	0.00
Number of energy projects	0.00	0.00	0.00	0.00	-
Number of other road projects	0.04	0.20	0.04	0.21	0.90
Number of other types of projects	0.00	0.00	0.00	0.00	-
Natural disasters					
Number of Natural disasters$_t$	0.00	0.00	0.01	0.11	0.01

Table 5: Communal-section level treatment effect on luminosity using $2.5km$ buffer

	Deblurred luminosity					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.201*	0.298***	0.101***	0.101***	0.073**	0.066**
	(0.105)	(0.036)	(0.035)	(0.035)	(0.033)	(0.033)
Observations	4,554	4,554	4,554	4,554	4,554	4,554
Number of CS	207	207	207	207	207	207
R-squared	0.005	0.059	0.144	0.146	0.177	0.178
Communal section FE	NO	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
Satellite FE	NO	NO	NO	YES	YES	YES
Contemporaneous covariates	NO	NO	NO	NO	YES	YES
Lagged covariates	NO	NO	NO	NO	NO	$t-1$

SE clustered at the communal section level between parentheses. *p$<$0.10; **p$<$0.05; ***p$<$0.01.

Treatment represents the coefficient β_1 from the regression following equation (1).

Table 6: Communal-section level treatment effect using alternative luminosity measures

	Deblurred data (1)	Raw data (2)	GRC (3)
Treatment	0.066**	0.104***	0.137**
	(0.033)	(0.030)	(0.055)
Observations	4,554	4,554	1,035
Number of CS	207	207	207
R-squared	0.178	0.477	0.498
Communal section FE	YES	YES	YES
Year FE	YES	YES	YES
Satellite FE	YES	YES	NO
Contemporaneous covariates	YES	YES	YES
Lagged covariates	$t-1$	$t-1$	$t-1$

SE clustered at the communal section level between parentheses. *p$<$0.10; **p$<$0.05; ***p$<$0.01.
Column (1) computes the treatment effect (β_1) from the regression following equation (1) using the deblerrud data according to the methodology proposed by Abrahams et al. (2016).
Column (2) uses the data from the Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS). The products are 30 arc second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude. Available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.
Column (3) uses an alternative measure of luminosity (Global radiance calibrated, GRC). https://ngdc.noaa.gov/eog/dmsp/download_radcal.html.

Table 7: Communal-section level treatment effect on luminosity using alternative specifications

	Alternative buffers					No PaP
	$2.5km$	$3.5km$	$5km$	No PaP	No CH	and no CH
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.066**	0.072**	0.058**	0.063**	0.058*	0.058**
	(0.033)	(0.029)	(0.026)	(0.030)	(0.030)	(0.029)
Observations	4,554	5,126	5,632	4,488	4,488	4,422
Number of CS	207	233	256	204	204	201
R-squared	0.178	0.168	0.166	0.187	0.180	0.191
Communal section FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Satellite FE	YES	YES	YES	YES	YES	YES
Contemporaneous covariates	YES	YES	YES	YES	YES	YES
Lagged covariates	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$

SE clustered at the communal section level between parentheses. *p<0.10; **p<0.05; ***p<0.01.

Treatment represents the coefficient β_1 from the regression following equation (1).

Specifications (1)-(3) use alternative buffers. Specifications (4)-(6) eliminate the communal sections that correspond to Port-au-Prince (PaP), Cap-Haïtien (CH), and both.

Table 8: Specification tests

	Parallel trend		Placebo outputs	
			Lag 90's output (no 2004-2005)	Random timing
	(1)	(2)	(3)	(4)
Treatment	0.111*	0.106*	0.069	0.001
	(0.060)	(0.061)	(0.059)	(0.003)
Ever treated before approval	0.051			
	(0.044)			
Placebo treatment date $t-1$		0.071		
		(0.054)		
Placebo treatment date $t-2$		0.027		
		(0.049)		
Placebo treatment date $t-3$		0.014		
		(0.051)		
Placebo treatment date $t \leq 4$		0.068		
		(0.048)		
Observations	4,554	4,554	3,726	4,554
Number of CS	207	207	207	207
R-squared	0.178	0.179	0.409	-
Communal section FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Satellite FE	YES	YES	YES	YES
Contemporaneous covariates	YES	YES	YES	YES
Lagged covariates	$t-1$	$t-1$	$t-1$	$t-1$
P-value	0.884			

SE clustered at the communal section level between parentheses. *p<0.10; **p<0.05; ***p<0.01.
Treatment represents the coefficient β_1 from the regression following equation (1).
Column (4) indicates a random allocation of the timing of the treatments.

Table 9: Communal-section level treatment effect on luminosity, heterogeneity

	Communal section classified by UBN, 2003			Minimum distance to PaP or CH		Years since approval	Approval/ completion
	Poorest	Poor	Least poor	$\leq 25km$	$> 25km$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.026	0.139***	-0.063	0.078	0.085**	0.024	
	(0.064)	(0.047)	(0.072)	(0.074)	(0.034)	(0.037)	
Treat. x years [1-2]						0.028	
						(0.037)	
Treat. x years [3-4]						0.072	
						(0.050)	
Treat. x years [4+]						0.223**	
						(0.086)	
Treat. since approval until completion							0.055*
							(0.032)
Treatment after completion							0.230**
							(0.081)
Observations	1,012	2,112	1,364	1,276	3,212	4,488	4,554
Number of CS	46	96	62	58	146	204	207
R-squared	0.241	0.250	0.167	0.230	0.201	0.180	0.182
Communal section FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Satellite FE	YES	YES	YES	YES	YES	YES	YES
Contemporaneous covariates	YES	YES	YES	YES	YES	YES	YES
Lagged covariates	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$
P-value equality of treatment	0.047			0.972			

SE clustered at the communal section level between parentheses. *p<0.10; **p<0.05; ***p<0.01.
Treatment represents the coefficient β_1 from the regression following equation (1).
Unsatisfied basic needs (UBN) obtained from MPCE (2004).

Table 10: Pixel-level treatment effect on luminosity using alternative specifications

	Alternative buffers					No PaP	
	$2.5km$	$3.5km$	$5km$	No PaP	No CH	no CH	GRC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.062***	0.059***	0.057***	0.062***	0.058**	0.057**	0.157**
	(0.022)	(0.020)	(0.016)	(0.023)	(0.022)	(0.023)	(0.070)
Observations	114,070	145,706	189,816	113,344	112,838	112,112	25,925
Number of Pixels	5,185	6,623	8,628	5,152	5,129	5,096	5,185
R-squared	0.020	0.017	0.016	0.021	0.022	0.022	0.331
Pixel FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Satellite FE	YES	YES	YES	YES	YES	YES	NO
Contemporaneous covarariates	YES	YES	YES	YES	YES	YES	YES
Lagged covar.	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$

SE clustered at the communal section level between parentheses. *p$<$0.10; **p$<$0.05; ***p$<$0.01.
Treatment represents the coefficient β_1 from the regression following equation (1).
Specifications (1)-(3) use alternative buffers. Specifications (4)-(6) eliminate the pixels that correspond to Port-au-Prince (PaP), Cap-Haïtien (CH), and both.

Table 11: Pixel-level Heterogeneous test

	$2.5km$ buffer			$3.5km$ buffer			$5km$ buffer		
	0-1km	1-2km	2-2.5km	0-1km	1-2km	2-3.5km	0-1km	1-2km	2-5km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.100***	0.067***	0.013	0.106***	0.077***	0.020	0.108***	0.091***	0.025*
	(0.031)	(0.025)	(0.025)	(0.031)	(0.026)	(0.020)	(0.031)	(0.023)	(0.014)
Observations	44,286	39,666	30,118	44,286	39,666	61,754	44,286	39,666	105,864
Number of Pixels	2,013	1,803	1,369	2,013	1,803	2,807	2,013	1,803	4,812
R-squared	0.035	0.020	0.011	0.035	0.020	0.010	0.035	0.021	0.010
Pixel FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Satellite FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Contemporaneous covarariates	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lagged covar.	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$	$t-1$
P-value	0.001			0.000			0.000		

SE clustered at the communal section level between parentheses. *p$<$0.10; **p$<$0.05; ***p$<$0.01.
Treatment represents the coefficient β_1 from the regression following equation (1).

Table 12: Panel regressions with satellite fixed effects

	Raw luminosity			Deblurred luminosity		
	$\ln(GDP)$ (1)	$\ln(GDP)$ (2)	$\ln(GDP)$ (3)	$\ln(GDP)$ (4)	$\ln(GDP)$ (5)	$\ln(GDP)$ (6)
$\ln(luminosity)$	0.060***	0.045	0.064**	0.075***	0.072***	0.082***
	(0.019)	(0.032)	(0.028)	(0.020)	(0.021)	(0.019)
Satellite FE	NO	YES	YES	NO	YES	YES
Earthquake	NO	NO	YES	NO	NO	YES
R-squared	0.369	0.606	0.727	0.461	0.677	0.796
Observations	29	29	29	29	29	29

Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table 13: Elasticities of DHS asset index and luminosity

	No CS FE	With CS FE		
	$\ln(DHS\_a)$ (1)	$\ln(DHS\_a)$ (2)	$\ln(DHS\_a)$ (3)	$\ln(DHS\_a)$ (4)
$\ln(luminosity)$	0.020***	0.047***	0.023**	0.025**
	(0.006)	(0.011)	(0.009)	(0.010)
Population	1.371***	2.057***	-0.970	-0.968
	(0.318)	(0.705)	(0.784)	(0.793)
Year FE	NO	NO	YES	YES
Satellite FE	NO	NO	NO	YES
R-squared	0.124	0.319	0.563	0.565
Observations	206	206	206	206

Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.