RAÚL ALFONSO VELILLA GÓMEZ

ESSAYS ON THE USE OF NIGHTLIGHTS TO MEASURE ECONOMIC PERFORMANCE

Thesis submitted to the Applied Economics Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Doctor Scientiae*.

Adviser: Alexandre Bragança Coelho

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Deus e a toda minha família.

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ABSTRACT

VELILLA GÓMEZ, Raúl Alfonso, D.Sc., Universidade Federal de Viçosa, February, 2022. **Essays on the use of nightligts to measure Economics Performance**. Adviser: Alexandre Bragança Coelho.

This thesis consists of three essays on the use of nightligts to measure economic activity in two developing countries. In the first essay, we analyze the effect of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) on economic activity in Brazil. The PPCDAm was an initiative of the Brazilian government that aimed to reduce the high rates of deforestation that the country was experiencing at the beginning of the 2000s. Although the program was directed directly to an environmental problem, it could indirectly have effects on economic activity since part of the productive activities in the Amazon are linked to deforestation. To do that, we use two empirical approaches: first, we compare the economic activity (measured as night light density) of municipalities inside and outside Brazilian Amazon before and after PPCDAm implementation in a difference in difference approach. Our results reveal that municipalities inside Amazon experiment a descrease in night lights intensity after 4 year of implementation of PPCDAm. Second, we exploit the geographical limits between Brazil and the other neighboring countries with which Brazil shares part of the Legal Amazon in order to estimate the effect of PPCDAm on economic activity. Specifically, we used regression discontinuity approach, which permits us to compare the economic activity, measured as the intensity of lights at night, on the border of the Brazilian Amazon Forest with its close neighbors. We estimated a regression discontinuity models year by year in order to understand the evolution of the economic activity before and after PPCDAm implementation. The results reveal that before the PPCDAm implementation the night light intensity in the Brazilian border was higher than its relative neighbors, however after the policy its neighbors experience high intensity during the three first years. In the second essay, we take advantage of a natural experiment - the creation of new Brazil capital (Brasília) in the decade of the 60's – and the subsequent construction of a new road system to analyze the persistence of public investment in road infrastructure on economic activity. The findings show that microregions located near the highway corridor experiment higher night light intensity relative to microregions far away. In the last essay, exploiting the international coffee price boom and municipal coffee intensity production, we study how commodities price shocks affect local economic activity in Colombia. Our results indicate that, on average, coffee-producing municipalities experience greater luminosity after the unexpected increase in international coffee prices than non-producing municipalities.

Keywords: Nighttime Light. Public Policy. Developing country.

RESUMO

VELILLA GÓMEZ, Raúl Alfonso, D.Sc., Universidade Federal de Viçosa, fevereiro de 2022. **Ensaios sobre o uso de luzes noturnas para medir o desempenho econômico**. Orientador: Alexandre Bragança Coelho.

Esta tese consiste em três ensaios sobre o uso de luzes noturnas para medir a atividade econômica em dois países em desenvolvimento. No primeiro ensaio, analisou-se o efeito do Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal (PPCDAm) sobre a atividade econômica no Brasil. O PPCDAm foi uma iniciativa do governo brasileiro que tinha como objetivo reduzir as altas taxas de desmatamento que o país vivia no início dos anos 2000. Embora o programa seja direcionado diretamente para um problema ambiental, este poderia indiretamente ter efeitos sobre a atividade econômica, uma vez que parte das atividades produtivas na Amazônia estão ligadas ao desmatamento. Para isso, utiliza-se de duas abordagens empíricas: primeiramente, compara-se a atividade econômica (medida como densidade de luz noturna) de municípios dentro e fora da Amazônia brasileira antes e depois da implantação do PPCDAm em uma abordagem de diferença em diferença. Os resultados mostram que os municípios da Amazônia experimentam uma diminuição na intensidade das luzes noturnas após 4 anos de implementação do PPCDAm. Em segundo lugar, a abordagem empírica para estimar o efeito do PPCDAm sobre a atividade econômica utiliza os limites geográficos entre o Brasil e os demais países vizinhos com os quais o Brasil compartilha parte da Amazônia Legal para estimar o efeito do PPCDAm sobre a atividade econômica.. Especificamente, utiliza-se um desenho de regressão descontínua, que nos permite comparar a atividade econômica, medida como a intensidade das luzes à noite, na fronteira da Floresta Amazônica brasileira com seus vizinhos próximos. Estimaram-se modelos de regressão discontínua ano a ano para entender a evolução da atividade econômica antes e depois da implantação do PPCDAm. Os resultados revelam que antes da implementação do PPCDAm a intensidade da luz noturna na fronteira do lado brasileiro era maior do que seus vizinhos, porém após a política os países vizinhos experimentaram alta na intensidade da luminosidade durante os três primeiros anos após a implementação da política. No segundo ensaio, aproveitamos um experimento natural - a criação da nova capital do Brasil (Brasília) na década de 60 - e a consequente construção de um novo sistema rodoviário, para assim analisar a persistência do investimento público em infraestrutura rodoviária na actividade economica. Os resultados mostram que microrregiões localizadas perto do novo corredor rodoviário experimentam maior intensidade de luz noturna em relação às microrregiões mais distantes. No último ensaio, analisando um boom dos preços internacionais do café junto com a intensidade produtiva no café de cada município, estudamos como os choques nos preços das commodities afetam a atividade econômica a nível local na Colômbia. Os resultados indicam que, em média, os municípios produtores de café experimentam maior luminosidade após o aumento inesperado dos preços internacionais do café do que os municípios não produtores.

Palavras-chave: Luz Noturna. Políticas públicas. País em desenvolvimento.

CONTENTS

Context

One of the most notable economic objectives of government policies is to create a favorable environment that generates growth and development. In other situations, economies are threatened or blessed by exogenous shocks to the economy. However, how do government policies and national institutions affect economic activity? How do exogenous shocks affect economic activity? Even though questions like that have been widely studied and are of great importance for policymakers, there is no widespread agreement on its answer. A growing body of literature attributes economic growth to the relevance of the national institutions (NORTH, 1991; ACEMOGLU; JOHNSON; ROBINSON, 2001, 2005).[1] In his seminal work, North (1991) argues that institutions are essentially important to economic performance. Acemoglu, Johnson, and Robinson (2005) document theoretically and empirically how differences in economic institutions caused differences in economic development. In particular, they argue that economic institutions, such as property rights, are important to economic outcomes because they influence both the economic incentives as well as the efficient allocation of resources. Acemoglu, Johnson, and Robinson (2001), using European mortality rates as an instrument for current institutions, show that settler mortality has a strong effect on the type of institutions. Specifically, they exploit the fact that Europeans colonizers chose to establish their settlements according to whether the place was free or not from diseases. Their findings reveal that colonies, where the European faced higher mortality rates, are less developed today than colonies that were colonized by Europeans. Recently, also analyzing African countries, Bates *et al.*, (2013) document the existence of a significant and systematic relationship between institutions and economic performance when they analyzed the history of political reform.[2]

On the other hand, government expenditure policies are considered one of the main driving factors for the long-lasting growth of national economies (BARRO, 1990; EASTERLY; REBELO, 1993; DEVARAJAN; SWAROOP; ZOU, 1996, among many others). Barro (1990), a pioneer in incorporating government expenditure into the

[1] See e.g. Rodrik, Subramanian and Trebbi (2004) and Haggard, Macintyre and Tiede (2008) for a review.
[2] See Fosu (2013) for an overview of institutions and economic outcomes in Africa.

economic growth analysis, shows that while a tax increase reduces growth, an increase in government expenditure raises it. In a similar vein, Easterly and Rebelo (1993) examine fiscal policy variables and growth rates using cross-section data from 1970 to 1998 of about 100 countries. They showed that the share of public investment in transport and communication is strongly correlated with growth in the majority of variables analyzed. Devarajan, Swaroop, and Zou (1996), analyzing 43 developing countries over 20 years, document a positive and significant effect on economic growth when the share of current expenditure is increased. A mounting body of evidence like that confirms this relationship.

Economies can be also blessed or cursed by unexpected shocks. For example, the economic environment of a country can be affected through discoveries of natural resources, climatic changes, shocks in the international prices of commodities, internal conflicts, natural disasters, among others. Several pieces of literature have documented how these shocks can affect economic activity for both low- and high-income countries as well as at the different levels of geographic aggregation. Recently, several scholars have focused their attention on examining how shocks in international commodities prices have influenced the local economy (see e.g., ACEMOGLU; FINKELSTEIN; NOTOWIDIGDO, 2013). Nevertheless, the theoretical and empirical research is already inconclusive in stating whether price increases, for example, have positive or negative impacts on the local economy. Acemoglu, Finkelstein, and Notowidigdo (2013) explore the exogenous variation in local areas incomes due to changes in global oil prices on health care spending in the United States. They found a positive and statistically significant income elasticity of hospital expenditure. Similarly, Brueckner and Gradstein (2016) also exploiting variations in international oil prices as an instrument for local income find a significant and positive effect on schooling attainment.

The three views of economic activity mentioned above share a particular similarity. These studies traditionally used the GDP or per capita GDP as a measure of economic activity at the national level. In contrast, few papers have analyzed whether the effects of government policies, national institutions, or price shocks vary at a more disaggregated level. The difficulty in this type of analysis is often related to the unavailability of data at the subnational level or in remote areas.

To fill this gap in the literature and to provide accurate estimations of the potential effects of government intervention and economic shocks on local economic activity, this thesis is a collection of three essays, which analyze three different contexts that could affect the economic activity in two developing countries. In the first essay, we evaluate the relevance of environmental institutions in Brazil by estimating the effects of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) on economic activity using the night lights intensity as a proxy. In 2004, the Brazilian government launched a policy to combat high deforestation rates. If the policy had an effect on reducing deforestation, we would expect economic activity in the areas where the policy is implemented to decrease because part of the economic activity in this area is associated with deforestation[3].The results indicate that the PPCDAm reduce the economic activity only in the 4th year after the policy was implemented. In the second essay, we estimate the long-run relationship of a massive investment in infrastructure carried out in Brazil on economic activity (1964-1985). We use the creation of Brasilia and the subsequent construction of the road network linking the new capital with the rest of the country as a source of exogenous variation and we estimate the relationship of the new highways on long-term economic activity. We find that microregions near to the new highway have larger average economic activity than the otherwise. In the third essay, we estimate the effect of commodity price shock on the local economic activity in Colombian municipalities. Exploiting the variation of international coffee price with the geographic distribution of coffee production in Colombian municipalities, we document that coffee producing municipalities experiment higher economic activity than non-producing municipalities. In particular, we try to answer the following questions. How do national institutions influence economic activity? How persistent are the economic benefits of public goods provision? How do exogenous commodities prices affect the local economic activity?

To do that, we use a novel measure of economic activity - the intensity of artificial lights at night. The use of luminosity data as a proxy of economic activity has been documented and tested in the pioneering work by Henderson, Storeygard, and Weil (2012). We could expect that most human activities in the evening, represented

[3] Although pasture expansion for extensive ranching has been the primary cause of forest loss in the Brazilian Amazon (ARAUJO, COSTA; SANT'ANNA, 2020), which is not an intensive activity in the use of electrical energy, other associated activities could reduce the use of night light. Economic sectors such as commerce and services could be affected by the decrease in deforestation, which could produce a decline in night light.

as more consumption and more production, required more artificial lights. This could be understood because the majority of goods used at night need lights. Therefore, we could assume that regions with more light intensity are regions or places with more economic activity (ELVIDGE *et al.*, 1997; DOLL; MULLER; MORLEY, 2006; CHEN; NORDHAUS, 2011). Consequently, we would expect that its income to be higher (HENDERSON; STOREYGARD; WEIL, 2012; LESSMANN; SEIDEL, 2017). In this order of ideas, it seems reasonable to assume that night-light can be used as a proxy of GDP for places where data are poorly measured or data are not available.

The use of luminosity data is attractive for several reasons. First, this data could help to deal with potential problems of no availability or little reliability that plague official data in some developing countries (HENDERSON; STOREYGARD; WEIL, 2012; CHEN; NORDHAUS, 2011; SUTTON; ELVIDGE; GHOSH, 2007). Second, luminosity data are available over time and for all places on Earth with uniform measure and over a very fine level of resolution. Finally, even though potential problems concerning measurement errors can appear related to how the satellite captures the lights, or climatic conditions, or human culture in the use of lights, this kind of measurement error is not correlated with traditional GDP data errors (PINKOVSKIY; SALA-I-MARTIN, 2016).[4]

This thesis consists of three chapters plus this introduction. In Chapter 1, we introduce the PPCDAm policy and the way that we assess its potential effects. Chapter 2, in its turn, presents how we examine the long-run effects of a massive investment program carried out in Brazil during the 60’s. Finally, Chapter 3 investigates the effects of an international commodity price boom in Colombia on the economic activity at the sub-national level.

[4] In spite of the fact that night lights data are very attractive for their availability and high geographic resolution and have been widely used in the economic literature, recently researchers have questioned the effectiveness of luminosity data as a measure of local development. According to Asher et al. (2021), Night light data are a highly statistically significant log-linear proxy for population, employment, per capita consumption, and electrification at a very tiny geographical level. They assert that the statistical significance is detected in both cross section and time series data. However, because night lights are linked with these variables, it is difficult to determine which of these variables is being measured from night lights alone (ASHER et al., 2021). We recognize that this may be a limitation for our study, and our results are interpreted with caution. In particular, we use the luminosity data as a proxy for economic activity for geographic levels where we do not have information on traditional GDP measurements. They are used as complements to traditional measures of economic activity and not as a substitute.

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Chapter 1
National Environmental Institutions and Local Economic Activity in Brazilian Amazon Forest

Abstract

The Brazilian government launched in 2004 the Action Plan for the Prevention and Control of Deforestation (PPCDAm) to reduce the high deforestation rates experienced at the beginning of the 2000s in the Amazon Legal. To do that, we use two empirical approaches. First, we compare the economic activity (measured as night light density) of municipalities inside and outside Brazilian Amazon before and after PPCDAm implementation in a difference in difference approach. Our results reveal that municipalities inside Amazon experiment a descrease in night lights intensity after 4 year of implementation of PPCDAm. Second, we use policy discontinuity at Brazilian borders with its neighboring countries with which it shares the Amazon and to identify the effect of PPCDAm on economic activity. We used the regression discontinuity approach, which permits us to compare the economic activity on the border of the Brazilian Amazon Forest with its close neighbors. We estimated a regression discontinuity models year by year in order to understand the evolution of the economic activity before and after PPCDAm implementation. We find that before the PPCDAm implementation the night light intensity in the Brazilian border was higher than its relative neighbors. However, after the policy, its neighbors experienced high intensity during the three first years.

JEL codes: Q50; Q58; O44

Keywords: Nighttime Light. Public Policy. Monitoring and Law Enforcement.

1.1. Introduction

The Amazon Forest, the largest rainforest on Earth, plays a major role in climate regulation, carbon storage, ecosystem services, biodiversity, and water supplies (HANSEN *et al.*, 2013). However, despite its worldwide environmental relevance, this region is constantly under threat of deforestation motivated mainly by economic benefits. In the last two decades, the average deforestation rate was near 15,000 km^2 (INPE, 2015). Although deforestation in the Brazilian Amazon Forest has decreased on average during the last two decades, fundamentally induced by the monitoring system and command and control policies, the pattern remains startling. Recent years have not been anything favorable and registers of setbacks in the goals of reducing deforestation have been evident since 2013 when the deforestation trend has shown upward. In 2009 the National Policy on Climate Change established a decrease in deforestation rates by 80% by 2020 (JUNIOR *et al.*, 2021). That is, until 2020 the deforestation goal was 3,925 km^2. However, the reality is different. It is estimated that by 2020, Brazil will clear about 11,088 km^2 (about 182% higher than the goal that was established in 2009).[5]

Despite the Federal Constitution and environmental laws clearly defining deforestation as an environmental crime[6], this is not always fulfilled due to the insufficient number of environmental prosecutors to cover the entire Amazon Forest, especially in the most remote areas like frontiers. Studying whether government institutions exert control over most remote areas - such as the Amazon Forest frontier - is a challenging task. This chapter studies this issue by evaluating the effects of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) on economic activity measured as the night light intensity in Brazil. In 2004, the Brazilian government launched the PPCDAm, which aimed to reduce the deforestation rates across municipalities belonging to the Legal Amazon.[7] The PPCDAm had as key action the introduction of the Real-Time System for Detection of Deforestation (DETER), satellites used to detect and locate deforestation activities in

[5] The data are estimated and correspond to about 45% of the monitored area, it is expected that the difference of this estimated value will be between more or less 58 - 303 km^2 (JUNIOR *et al.*, 2021).
[6] Brazilian Federal Constitution - Art. 225 and Law N° 9.605 of February 12 of 1998.
[7] The Legal Amazon is composed by 775 municipalities, which belong in their totality to the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins, Mato Grosso and some municipalities of the state of Maranhão (SUDAM, 2010).

real-time.[8] Once an illegal deforestation activity is detected, alerts are sent to several government institutions that move to the area for identifying the authors and applying sanctions.[9,10]

Despite several studies that documented a significant decrease in deforestation rates after PPCDAm implementation (HARGRAVE; KIS-KATOS, 2013; ASSUNÇÃO; GANDOUR; ROCHA, 2015), little is known about the relevance of the national institutions in this regard. To the best of our knowledge, Burgess, Costa, and Olken (2018) are the first work that assesses the relevance of deforestation policy in Brazil comparing with other countries. We follow their approach to identifying the relevance of Brazilian institutions through an evaluation of PPCDAm policy. Although Burgess, Costa, and Olken (2018) evaluate the same policy, we take a different point of view and we evaluate the PPCDAm on economic activity. For that, we use the night-light intensity as a proxy of economic activity. The use of night-light is important in this context since in the tropical forest area a share of the economic activity is associated with illegal extraction (BURGESS; COSTA; OLKEN, 2018) and the informal sector, which normally is unregistered economic activity in traditional surveys (GHOSH *et al.*, 2009; TANAKA; KEOLA, 2017).[11,12] Thus, night-light is relevant for studying economic impacts in Brazil where informal employment represented about 31% in 2017, overcoming even formal jobs (IBGE, 2018).[13] On the other hand, although it is not our main objective, we also contribute to understanding in which way the relationship between deforestation and economic activity takes place.[14] Given that the PPCDAm policy had an objective to reduce deforestation, one could think that it is not correlated

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[8] The DETER was developed by the National Institute for Space Research (INPE).

[9] The Brazilian Environmental Protection Agency (IBAMA), the Brazilian Army, the Federal Police and Highway Federal Police act jointly in carrying out these operations.

[10] See section 1.2 for an exhaustive detail of this policy.

[11] Ghosh *et al.*, (2009), estimating Mexico's informal economy by nighttime satellite imagery, document that the informal economy and inflow of remittances could be around 150 percent larger than the information provided about the Gross National Income. Tanaka and Keola (2017), comparing sales data about formal and informal of non-farm sectors in Cambodia with changes in nighttime for 1993-2010, found that both formal and informal firms increased their estimated sales. They also show that share of informal sales increased from 68.8 per cent to 76.6 per cent in the period.

[12] See La Porta and Shleifer (2014), Schneider and Enste (2000), and Schneider (2005) for a review of the informal economy.

[13] A potential limitation of our study is that night lights are linked with variables like per capita consumption, employment, population, and electrification, and it is difficult to determine which variables are measured with night lights separately (ASHER et al., 2021).

[14] The empirical evidence has documented that the relationship between deforestation and economic growth could go in both ways. Policies that incentive the market's promotion and increase openness to trade might lead to an increase in the forest cover, while in the absence of strong policies that protect the environment, forest cover might decrease with economic growth (FOSTER; ROSENZWEIG, 2003).

with night-lights. Thus, we can use this policy to estimate the causal relationship with economic activity. We begin our research design analyzing whether PPCDAm policy has effects inside Brazilian municipalities. The policy itself generates two groups, since it is applied only to the municipalities within the Brazilian Amazon. Thus, we consider the municipalities within as treatment and those located outside the Amazon as a control group. We compare municipalities inside Brazilian Amazon with municipalities outside before and after the policiy implementation using a difference in difference approach. Then we analyze the effect of politics between countries. Specifically, we analyze the border between Brazil and the neighboring countries with which Brazil shares the Amazonian territory. Once the policy is directed within the Brazilian territory and not in its neighbors, we have a discontinuity in the geographical borders. To do it, we use a regression discontinuity design, which permits us to compare the economic activity, measured as the intensity of lights at night, on the border of the Brazilian Amazon forest with its close neighbors. To analyze the behavior of economic activity before and after the implementation of PPCDAm, we perform estimates year by year between 2000 and 2013.[15,16] Thus, whether the PPCDAm has effects on deforestation rates as Burgess, Costa, and Olken (2018) showed, we could expect a decrease in the intensity of the night-lights after the policy implementation in Brazil but no changes in the other countries relative to a prior period of implementation.[17]

We begin by providing meaningful evidence of the influence of the PPCDAm inside Brazil. We explore the effect of PPCDAm on night lights across municipalities inside and outside Brazilian Amazon, using a difference in difference approach. Municipalities inside Amazon experiment a descrease in night lights intensity after 4 year of implementation of PPCDAm. Then, we look the effects of PPCDAm at country level using a regression discontinuity desing. Our results show that, using bandwidth of 25 kilometers from the Brazilian border, it seems to be no difference in night lights density between Brazil and others neighboring both before and after PPCDAm. This

[15] Brazil shares Amazon Forest with eight countries: Colombia, Bolivia, Venezuela, Peru, Guyana, Guyana French, Equator, and Suriname.

[16] The Amazon Forest area is defined by La Red Amazónica de Información Socioambiental Georreferenciada (RAISG, by its acronym in Spanish).

[17] Waroux et al. (2019) argue that increases in public or private deforestation restrictions may negatively affect certain regions or certain sectors. In particular, they explain that deforestation laws, whether public or private, can lead to a shift in agricultural activity and deforestation to unregulated or less regulated areas. In our context, individuals engaged in deforestation-related economic activities on the Brazilian side of the border have an incentive to move to nearby areas outside of Brazil to avoid penalties. In this case, our estimates may be biased.

result changes when we consider a 100 kilometers bandwidth. In particular, our estimates, considering badwind of 100 kilometers, imply that night light density decrease within Brazil compared to its neighboring counterparts durint the first three years after PPCDAm implementation.

The finding is this chapter seeks to contribute to a vast strand of literature. First, on the literature about the importance of national institutions on economic and ambiental outcomes. For example, the influencial study of Burgess, Costa, and Olken (2018) which evaluated the PPCDAm on deforestation rates and found that after the policy implementation, Brazilian deforestation rates have equaled its close neighbors.[18] This is an interesting result, which reveals a control ability that the government can exert even in the most remote areas. We view their work and ours as complementary.

Most closely related to our study are the contributions of Michalopoulos and Papaioannou (2014), Pinkovskiy (2017), and Egger, Koethenbuerger, and Loumeau (2017). These papers study the role of national institutions across a particular border on economic activity measured as light night density. In particular, Michalopoulos and Papaioannou (2014) assess how much the national institutions matter over economic activity, analyzing the changes in night-light at the border in several African countries. Similarly, Egger, Koethenbuerger, and Loumeau (2017) using reforms that joined municipalities in Germany evaluated the effects of changes in a local border on economic activity (their measure of economic activity is also night-light density). Pinkovskiy (2017), in his turn, analyzed in several countries the existence of discontinuities in the short and long-run growth rates of the per capita light night intensity across national borders. In contrast to these studies, we contribute to this literature by analyzing how the power of environmental institutions influences economic activity. More specifically, understanding how environmental policies affect the behavior of the economic agents is relevant for policymakers to construct a compensation mechanism given the big dependence of economic agents of natural resources associated with Amazon.

[18] Before the PPCDAm implementation (between 2001 and 2005), Brazilian deforestation rates reached more than three times the rates experienced in their neighbors near to the border and then in the year that followed the implementation of the policy this rate was the same across different countries (BURGESS; COSTA; OLKEN, 2018).

The rest of the chapter is organized as follows. In section 2, we provide the historical background of the institutional context. Section 3 provides a literature review. Section 4 presents the theoretical framework. Section 5 describes the empirical strategy and the main data sources. Section 6 discusses the descriptive statistics and main results. Finally, section 7 concludes.

1.2. Institutional Context

The Amazon Forest, the largest rainforest on the Earth with around 5.5 million square kilometers, plays a major role in climate regulation, carbon storage, ecosystem services, biodiversity, and water supplies (HANSEN *et al.*, 2013). Nevertheless, its environmental importance does not seem to make it worthy of its conservation and preservation of human activities. Brazil has been considered the world leader in deforestation (NEPSTAD *et al.*, 2009), and, recently the deforestation rates have once again caught the attention of the international scientific community.[19]

The main cause of Brazilian Amazon deforestation is associated with diverse drivers, which can date back to the 1960s.[20] In the '60s, the military dictatorship promoted large projects to expand infrastructure and settlements with the aim of securing national borders and integrating the region into the national economy, which caused a wave of significant clearing (ARAUJO *et al.*, 2009; ANDERSEN *et al.*, 2002; LAURANCE; ALBERNAZ; DA COSTA, 2001).[21] By the 1980s, the deforestation dynamic was associated with the agricultural sector. Increments in agricultural credit and subsides, together with the access to globalized markets and better transport conditions caused an acceleration in the agribusiness sector that was reflected in increased deforestation rates (HARGRAVE; KIS-KATOS, 2013; PAILLER, 2018). By the early 1990s, the agribusiness sector was already producing on a large scale and deforestation rates grew with economic activity, especially after the monetary reforms that stabilized the economy of high inflation rates (FEARNSIDE, 2005) as well as the

[19] Approximately 60% of total Amazon Biome is within Brazilian territory.
[20] Before the 1960s, the Amazon region was occupied by native populations. Access to the forest was open and economic activities were linked to some extraction activities (rubber and nuts), but were basically based on the subsistence of already established populations.
[21] Early in the 1960s, the Brazilian government launched an infrastructure program that aimed to connect the Amazon region with the rest of the country. More than 60,000 kilometers of roads were built which caused a settlement of people in the areas surrounding the roads, increase in the real GDP, and an increase in deforestation. In particular, between 1972 and 1985 the total population increased from 7.3 million to 13.2 million, the real GDP went from \$2.2 billion to \$13.2 billion and 33 million hectares of forest were converted to agricultural land (ANDERSEN; REIS, 2015).

incorporation of the Brazilian economy into international soy and meat markets (ARIMA *et al.*, 2014; MARGULIS, 2003). In the mid-'90s, high rates of deforestation drew attention and environmental policies were part of the national agenda. As an immediate action, the federal government increased from 50 to 80 percent of forest cover on private lands, which became mandatory.

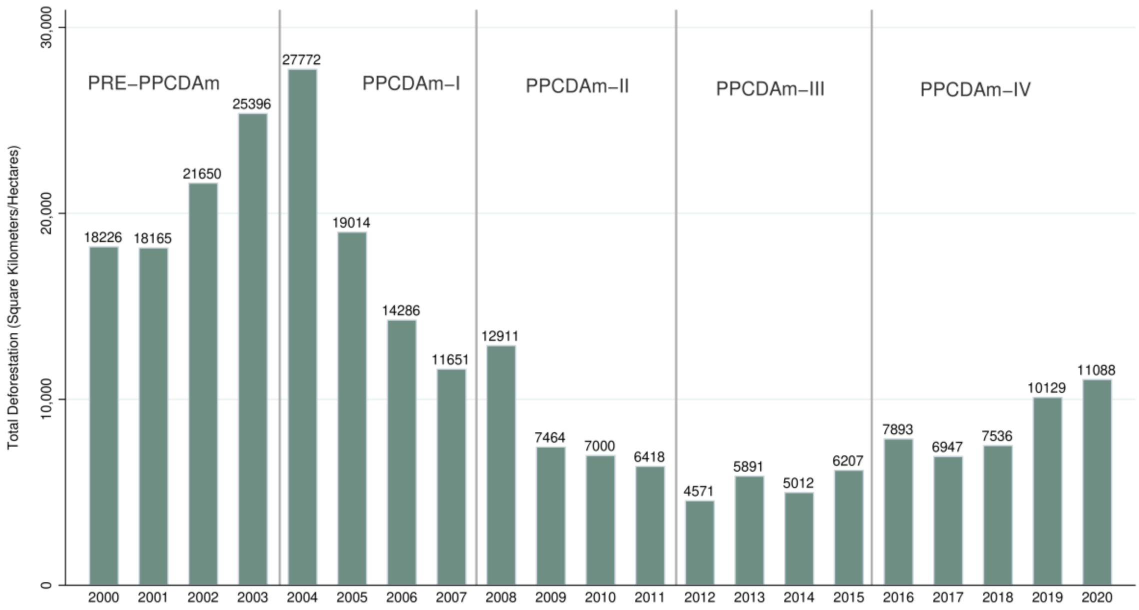
However, deforestation in the Brazilian Amazon is not a thing of the past. In 2004, the annual deforestation rates reached an alarming peak when more than 27 thousand square kilometers of the forest were cleared (See Figure 1.1) (PRODES, 2021).[22] Given these alarming rates, the Brazilian federal government and the Ministry of the Environment (MMA) began to articulate a set of policies to preserve and promote forest conservation, whose main focus was on three aspects: (i) strengthening monitoring and law enforcement; (ii) expanding protected territory; and (iii) adopting a conditional rural credit policy. This initiative was the beginning of a restructuring of Brazilian environmental policies, of which we highlight the years 2004 and 2008 as extremely important years for the change of policies. Since then, the Amazon deforestation problem became part of the highest level of the federal government's political agenda (BRASIL, 2012).

1.2.1. Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm)

In 2004, as part of a set of measures to reduce the growing trend of deforestation rates in the Amazon area, the Brazilian government launched the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm, for the Portuguese-language acronym). PPCDAm was the response that the Brazilian government implemented to the National Institute for Space Research (INEP) report which indicated an increase of about 40% in deforestation between July 2001 and August 2002 (see Figure 1.1).

[22] Figure 1.1 shows that the total deforestation rate in the Brazilian Amazon reached a peak in 2004 and then a downward trend is evidenced until 2012 where the greatest reduction in recent times was experienced, reaching 4571 km2 (84% less than if we compared with its high peak in 2004).

Figure 1.1: Total Deforestation in Brazil (2000-2020)



Note: Brazilian Amazon Deforestation 2000-2020. Gray lines inside the graph divide the graph according to each phase of the PPCDAm. Source: Authors elaboration from INEP data.

The PPCDAm was the result of an inter-ministerial initially composed of 13 ministries of the federal government, under the direct coordination of the President's Chief of Staff (Decree of July 3, 2003), which have the function of proposing actions that help reduce tropical clearings.[23] PPCDAm was the starting point for changing the way sanctions were applied to deforestation and how the enforcement of environmental regulations should be executed. The program prioritized mainly four thematic axes: (i) Land Tenure and Territorial Planning; (ii) Environmental Monitoring and Control; (iii) Fostering Sustainable Production, and; (iv) Sustainable Infrastructure Development (Casa Civil, 2004; MMA, 2013).[24] This set of activities involved the integrated participation of federal, state, and municipal governments (MMA, 2008; IPEA *et al*., 2011).[25]

A key action of the PPCDAm was the introduction of the Real-Time System for Detection of Deforestation (DETER) developed by the National Institute for Space

[23] In March 2013, this competence was transferred to the Ministry of the Environment under Decree 7957.
[24] The Sustainable Infrastructure Development axis was removed from the PPCDAm in 2005 (one year after the PPCDAm was implemented). However, this axis was integrated later to the Sustainable Amazon Plan.
[25] Initially, the plan was divided into three phases, however recently a fourth phase was added to give continuity to the plan.

Research (INPE) by the Monitoring the Amazon Gross Deforestation Project (PRODES) (ALMEIDA *et al.*, 2016).[26] The DETER product is based on satellite imagery on the forest with a high temporal resolution of nearly daily coverage. These data allow detection and georeferencing of deforestation hot spots in areas greater than 25 hectares in real-time.[27]

Once a deforestation threat is detected, alerts are sent to the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) which is the institution that acts as the national environment police and subsequently enforces the law (INPE, 2008; (ANDERSON *et al.*, 2005).[28] The IBAMA agents, together with federal police, move to the area for identifying the authors and applying sanctions (DINIZ *et al.*, 2015).[29,30] Simultaneously to the DETER implementation, IBAMA increased substantially the number of agents, improved staff recruitment, and invested in training (ASSUNÇÃO; GANDOUR; ROCHA, 2015). This allowed for greater efficiency in the detection of hotspots as well as law enforcement to offenders.[31]

During the first phase of the PPCDAm, there were important advances in the land property axis also. We can highlight the creation of 50 million hectares of protected areas located along deforestation frontiers, the homologation of 10 million hectares of indigenous territories, and declaring invalid approximately 60 thousand illegal land titles (Abdala, 2008; (ASSUNÇÃO; GANDOUR; ROCHA, 2015).[32]

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[26] PRODES Project uses Landsat data.

[27] The DETER data system was an innovation in the deforestation field in Brazil to be able to take government actions according to the real time of forest clearing, government actions are unlikely to be taken based on annual data. To overcome this limitation, the DETER system generates the imagery data in an interval of 15 days (ASSUNÇÃO; GANDOUR; ROCHA, 2015). However, since 2011 the INPE starting to process data to daily frequency, so updated the information on recent deforestation data to IBAMA every week.

[28] IBAMA was created in 1989 and since then has acted as the institution that is responsible for environmental monitoring and law enforcement in Brazil (ASSUNÇÃO; GANDOUR; ROCHA, 2015).

[29] As a complement to PPCDAm, in 2007 the INEP launched the DEGRAD, a monitoring system for forest degradation detention based on Landsat and CBERS satellite imagery and a Minimum Mapping Unit of 6.25 hectares (DINIZ *et al.*, 2015). This system allows detecting deforestation where forest cover was not completely removed.

[30] Previous to the implementation of the DETER satellite system, the monitoring of deforestation in the Amazon depended on voluntary reports from civil society. This mechanism was rarely effective because the agents could not reach the places where deforestation was being carried out in a timely manner. Thus, this mechanism limited law enforcement.

[31] This is a significant advance to enforce environmental laws in Brazil because it is important to catch infractors red-handed in order to successfully enforce the law.

[32] The Protected Areas Program was established though Decree 4326 of 2002.

After notable progress in land titling and planning axis as well as environmental monitoring and control axis, in 2007, a resurgence in deforestation was noted. An increase of 12% in deforestation rates incentive the federal government to accelerate the implementation of a set of measures in areas suffering the most severe deforestation. In front of that, in January 2008, the second phase of PPCDAm (2008-2011) was released. A “municipality blacklist" was announced, which consisted of 36 municipalities where 45% of amazon deforestation was concentrated (ASSUNÇÃO; ROCHA, 2019; WEST; FEARNSIDE, 2021).[33,34] These municipalities were named Priority Municipalities (*Municípios Prioritários or MPs*) and the strategy consisted of taking differentiated actions for these municipalities with outstanding historical deforestation rates to reduce these rates as soon as possible. Several criteria were taken into account to incorporate the municipalities into this blacklist, namely: accumulative area of forest lost, total forest area cleared recently over the last three years, and the recent increase in the deforestation rates in at least three of the last five years (Civil, 2009). The Ministry of the Environment conducts inspections annually and any municipality of the legal Amazon can integrate this list if it has these requirements, and they can exit if they reduce the deforestation rates.

Municipalities listed were exposed to more rigorous environmental surveillance, reduced deforestation license, the embargo of illegally cleared areas, and limited subsidized rural credit and market access (FEARNSIDE, 2017). Following this strict surveillance, between 2007 and 2008, the number of embargo properties in blacklisted municipalities increased by 53% compared with the increase of 11% in non-blacklist. On the other hand, the number of environmental fines awarded increased by 13% in blacklisted municipalities compared to the immediate previous year while a decrease in fines by about 10% was evidenced in unlisted municipalities (ARIMA *et al.*, 2014).[35]

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[33] The municipalitiy’s blacklists were announced under Decree 6321 of 2007. The objective was to draw up a strategy to control and monitor illegal deforestation to prevent land degradation. The list started with 36 municipalities, but in 2009 and 2011 new 7 municipalities were added and two in 2012, for a total of 52 municipalities included in the list. Surprisingly, only 11 municipalities reduced their deforestation rates and were off the blacklist.

[34] Considering that the Amazon Biome consists of 547 municipalities and, that 46% of deforestation is concentrated in 36 of these, is something alarming. In other words, 46% of deforestation were concentrated in 7% of municipalities.

[35] Although efforts to enforce the law through command-and-control mechanisms, the environmental fines applied appear to be relatively low. Between 2005 and 2009 were applied 24,161 fines (around US$ 7.34 million) by the IBAMA, however only 6% of these revenues was collected (SOUZA-RODRIGUES, 2019).

There has been anecdotal evidence suggesting that municipalities suffered from some non-policy penalties. Producers caught illegally deforesting are subject to having their production confiscated and destroyed, their land seized, and all machinery used for this illegal activity destroyed or learned and subsequently auctioned (GANDOUR, 2018). Also, deforestation agents suffer from economic sanctions applied by the supply chains of essential products (GANDOUR, 2018) as well as the political reputation of the mayors was affected (ABMAN, 2018), which in some cases led to affect potential re-election or compromised the power of the political party in the next elections.

1.3. Theoretical Framework

In this study, we built a framework grounded in the model developed in Burgess, Costa, and Olken (2018), which was based on Turner, Haughwout, and Van Der Klaauw (2014), to provide support to our empirical strategy. The model is static and assumes a heterogeneous plot of land over a line, in where each pixel $x \in [-1,1]$ is a parcel of land. In addition, x is an index and it takes a value of one if it is covered for native vegetation. The inhabitants are scattered across the pixels uniformly and there are two possible options of using the land. First one, they can choose to preserve the land in which the index takes a value of zero. On the second one, they can use the land as an input to produce and, consequently, deforest. The economic agents chose produce because the output leaves them wealth. Therefore, each individual can choose how much capital she/he uses to produce. Burgess, Costa, and Olken (2018) also assume that the pixels are productivity heterogeneous. The gross product in pixel x, using capital $k_x \geq 0$, is represented as $A(x, k_x)$. In addition, this function is assumed continuous with respect to x and capital has diminishing returns.

Now, assume two countries L and R in which land is extended over them. The pixel $x < 0$ belongs to country L and $x \geq 0$ belongs to R. Burgess, Costa, and Olken (2018) also assume that each country has different regulations in the use of the land. Taken this together, the pixel productivity net of regulation could be expressed as $f(x, k_x) = A(x, k_x)V(x)$. $V(x)$ can take two possible values, namely:

$$V(x) = \begin{cases} v_L & if\ x < 0 \\ v_R & if\ x \geq 0 \end{cases} \quad (1.1)$$

where v_L, $v_R \in [0,1]$.

As we mentioned before, the individuals choose to use the land or not for production activity. If they choose to use the land, they also choose the quantity of capital. Indeed, individuals choose the capital k_x^* that maximizes the private profit, which they use to buy consumer goods that generate economic growth. Following Burgess, Costa, and Olken (2018), the profit function is given by:

$$\pi(x, k_x) = A(x, k_x)V(x) - rk_x \tag{1.2}$$

where r represents the capital price. Thus, conditional to the production, the optimal capital implement in pixel x is

$$k_x^* = \underset{k_x \geq 0}{argmax}\ \pi(x, k_x) \tag{1.3}$$

Thus, when $\pi(x, k_x) < 0$, we can assume that no economic activity is carried in pixel x, no capital is used and the area is preserved.

Now assume that we can observe the production $f(x, k_x)$ for each pixel and run a spatial discontinuity at the border. The comparison of log of productivity of each pixel on two sides of the border and the closest to $x = 0$ can be expressed as:

$$\lim_{x\to 0+} lnf(x, k_x^*) - \lim_{x\to 0-} lnf(x, k_x^*) = \underbrace{\lim_{x\to 0+} lnA(x, k_x^*) - \lim_{x\to 0-} lnA(x, k_x^*)}_{\phi} + \underbrace{lnv_R - lnv_L}_{\rho} \tag{1.4}$$

where ϕ represents the combination of differences in pixel productivity and optimal capital use on each side of the border. The parameter ρ could be understood as the local difference of the direct cost of land regulation on productivity. In addition, Burgess, Costa, and Olken (2018) take into account the fact that the optimal capital choice, k_x^*, could be different on both sides of the border. Consequently, if $k_L^* \neq k_R^*$, so we cannot assume that $\phi = 0$.

1.4. Empirical Strategy

To evaluate the power of environmental Brazilian institutions on economic activity, we exploit both geographic discontinuities generated by the PPCDAm policy across the Brazilian administrative boundary as well as its implementation date. Our empirical analyses rely on two different methodologies: Differences-in-differences design (diff-in-diff) and Regression discontinuity design (RDD).

1.4.1. The Difference in Difference Estimation (diff-in-diff)

We begin our empirical application by analyzing whether PPCDAm policy has effects within Brazilian territory. To do so, we explore the fact that the PPCDAm policy affects or is only applied to municipalities that belong to the legal Amazon. The police itself generates a distribution in two groups of municipalities, those that are reached by the policy because they are part of the legal Amazon and those that are not reached because they are located outside the legal Amazon. This division allows us to create a group that we call a treatment (those municipalities within the legal Amazon) and a control group (those outside the legal Amazon).

The diff-in-diff approach compares the changes in outcome variable in the treatment areas before and after the intervention to the changes in outcome variable in the control areas. Comparing these changes permits us to control for observed and unobserved time-invariant characteristics that could be correlated with our dependent variable. In particular, we employ the following baseline specification:

$$y_{it} = \rho(Treatment_i \times Post) + \beta Time \times Z_i + \eta_i + \theta_i + \varepsilon_i \tag{1.5}$$

where y_{it} is the dependent variable of interest (Night Light Density) for municipality i in year t.[36] The independent variable of interest is the interaction of $Treatment_i$ which indicates whether the municipality is part of the legal Amazon or not, and $Post$, which implies post-intervention observation started in 2004. The key parameter of interest is ρ and captures the effect of PPCDAm on the night light density. The equation also includes interactions between baseline municipalities' characteristics (Gini index, population in 1991, and GDP in 1991) and time trends. This allows us to control for possible differential trends associated with these factors. Furthermore, we control for municipalities fixed effect η_i to control for constant unobserved factors across municipalities and control for year fixed effects θ_i. Finally, use robust standard errors

[36] In this empirical approach (difference-in-differences model) where we use municipalities within the Amazon as treatment and outside the Amazon as control, we use the sum of all brightness pixels within each municipality as our dependent variable. In these sections, we use data on luminosity from the year 2000 to 2013. In particular, the independent variable was constructed as follows in the following equation:

$$light_{mst} = \sum_{i=0}^{63} \times (\# \; of \; pixels \; in \; municipality \; m, state \; s, and \; year \; t \; with \; DN = i)$$

See Equation (1.9) for more details.

for clusterings at the microregion level to control for potential serial correlation (BERTRAND; DUFLO; MULLAINATHAN, 2004).

Event Study Design

A limitation of the previous approach based on Equation 1.5 is that it does not provide any insight into the timing in which the policy takes effect. An estimate of the difference-in-difference model estimates the average effect of the policy, which may be different over time. To evaluate how our variable of interest evolved over years surrounding the policy implementation, we employ a flexible event-study design. Thus, the event-study specification takes the form of:

$$y_{it} = \alpha + \sum_{\tau=-2}^{\tau=-T} \rho_{pre}^{\tau}\ 1(t = -\tau) \times Treatment_i +$$

$$\sum_{\tau=0}^{\tau=T} \rho_{pre}^{\tau}\ 1(t = \tau) \times Treatment_i + \beta Time \times Z_i + \eta_i + \theta_i + \varepsilon_i \qquad (1.6)$$

where $1\ (t\ = \cdot)$ are indicators for year τ. The omitted category is -1. The other variables are the same ones used in Equation 1.5. The year zero is 2004 when the PPCDAm was implemented. In this setting, the parameter of interest is ρ^{τ} , which allows us to evaluate how our interest outcome evolves over the years surrounding the PPCDAm implementation and thus estimate the timing of the effect. Thus, this specification provides us a more detailed picture of the relationship between PPCDAm and Night Light density.

The identifying assumption of this framework is that in the absence of the PPCDAm, municipalities in the treatment and control group would have experienced similar trends in the night light intensity. Thus, any change immediately after the policy implementation would provide strong evidence that these changes were caused by the policy rather than by unobserved factors.

Other Related Outcomes

PPCDAm policy could affect economic activity through other related outcomes. To shed light on the relative importance of potential difference explanations, we carry out alternative regression to estimate how the PPCDAm affects variables that could affect our measure of economic output. Specifically, we estimate equations similar to Equation 1.5 but using variables capturing these related outcomes variables as the dependent variable. More specifically, we estimate the following equation:

$$C_{it} = \rho(Treatment_i \times Post) + \beta Time \times Z_i + \eta_i + \theta_i + \varepsilon_i \quad (1.7)$$

where C is the CO_2 emissions in the municipality i in the year t (2000 and 2010), instead of night light density. The rest of the specification is equal to that presented in Equation 1.5. The PPCDAm could affect the Night Light density across its effect on CO_2 emissions. We hypothesize that if the PPCDAm policy has effects on deforestation (its main objective), that is, it reduces deforestation rates, then it would reduce carbon dioxide emissions. Once we have lower rates of carbon dioxide emissions - which has been documented to be positively correlated with economic activity - we could expect the luminosity to decrease with the PPCDAm policy.

1.4.2. Regression Discontinuity Design (RDD)

The RDD, in its turn, relies on a discontinuity in treatment assignment to assess the impact of the policy. We use a spatial RDD, which is an extension of a traditional single-dimensional RDD.[37] By comparing night lights' density of pixels located just inside of Brazilian geographic boundaries with those located just outside, it is possible to identify the causal effect of the policy.

Although the PPCDAm policy treatment is determinate by a deterministic and discontinuous function of longitude and latitude variables - which suggests estimating the policy effects using a regression discontinuity design with a multidimensional threshold-, we collapse the spatial data into a single dimension and use "the distance to the border" as a running variable.[38,39] Thus, positive values of the running variable

[37] See e.g., Holmes (1998); Black (1999); Pence (2006); Dell (2010); Magruder (2012), and Ito (2014) for applications of geographic or spatial regression discontinuity design.
[38] Dell (2010); Dell, Lane, and Querubin (2015); Dell and Querubin (2016), and Kumar (2018) provide applications of spatial RDD with multidimensional discontinuity in longitude-latitude space as a running variable.
[39] See Black (1999) and Holmes (1998) for a similar approach.

are pixels in the Brazilian Amazon forest, while negative values represent pixels outside. In particular, we will employ the next specification:

$$y_{it} = \beta' X_i + \alpha BRA_i + \rho(f(DistBorder_i) \times Post) + \varepsilon_i \tag{1.8}$$

where y_{it} is the light night density in the pixel i. BRA_i is a dummy variable that takes value one if the pixel i belongs to Brazil and zero otherwise. The independent variable of interest is the interaction between $f(DistBorder_i) = BRA_i \times f^{BRA}(DistBorder_i) + (1 - BRA_i) \times f^{Outside\_BRA}(DistBorder_i)$ which is a polynomial of distance from the border, and "$Post$" which denotes post-intervention observations starting in 2005. We also incorporate a vector X_i of control variables that include the average of the slope, elevation, temperature, rainfall and, soil quality for each pixel i in year t. The parameter of interest is ρ, which captures the change in the effect of the PPCDAM at the discontinuity between the pre– and post-intervention policy. Additionally, robust standard errors will be corrected for clustering at the country level (BERTRAND; DUFLO; MULLAINATHAN, 2004).

The basic assumption required to interpret the causal effect of PPCDAm on the economic activity is that all factors related to the outcome are either evolving smoothly (continuously) concerning the running variable as in standard RDD design (IMBENS; LEMIEUX, 2008) or its discontinuity is constant over time. To validate our empirical strategy, we divide the empirical analysis into three parts.

First, our identification strategy would be threatened if the individuals can manipulate the running variable. Nonetheless, given that Brazilian geographic limits were defined by The Treaty of Madrid between Portuguese and the Spanish Crowns in 1750, it does not seem plausible that this identifying assumption will be violated. Another key assumption that we will test is whether all relevant factors besides treatment are evolving continuously at the Brazilian border. To do so, we estimate an RDD design with the covariates as a dependent variable after and before the PPCDAM. We do this analysis for different covariates: slope, elevation, temperature and, rainfall. We hope that no evidence of unbalanced covariates around the boundaries will be found. The idea is that very close to the border, the geographic characteristics should be the same.

Second, as in the standard diff-in-diff design, the key identifying assumption is that in the absence of the PPCDAm, areas in the treatment and control groups would have experienced the same trends in the night-light density variable. This assumption would be violated only if there were differential trends in time-varying determinants of outcomes across treated and untreated areas. To provide suggestive evidence on the validity of this assumption, we control for the interaction of different pre-treatment municipality characteristics with a linear time trend. Thus, if the secular trends were the same in the absence of treatment (pre-intervention period), then it seems plausible to think that they would be the same in the post-intervention period if the intervention did not happen.

Finally, the effect of the PPCDAM policy at the Brazilian boundaries could be confounded with similar policies in neighbors' countries. To the best of our knowledge, there are no similar policies in any of the countries with which Brazil shares the Amazon Forest in our study period.

1.4.3. Data Sources and Data

Nighttime Lights

Luminosity data will come from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) provided by the National Oceanic and Atmospheric Administration (NOAA) since the 1970s. Nevertheless, data are available digitally from 1992 to 2013. Each satellite observes each place on Earth every night between 8:30 to 10:00 pm local time. Data are collected and saved in a digital number (DN), which ranges from 0 to 63 with a resolution of 30 arc-second area pixels, or approximately 0,86 square kilometers at the equator.[40] The dataset covering 75◦N to 65◦S latitude and 180◦W to 180◦ longitudes. They are processed overlaying all daily images obtained during the calendar year, removing ephemeral lights like lightning and forest fires, those light that are shrouded by clouds or overpowered by the aurora or solar glare (near the poles), and other factors that can confound the results. We take advantage of the availability of these datasets in the most remote areas in the Amazon Forest with the same unit measure and resolution, which allow us to explore the change of light night intensity as inside as outside of Brazil.

We use separate intensity measures in luminosity for our two empirical approaches. On the one hand, we use the sum of the luminosity of each pixel within

[40] Note that the luminosity intensity ranking is between 0 and 63, where a value of 0 means no light and 63 the largest luminosity.

each Brazilian municipality for each year. We use this measure of luminosity in our first empirical approach (the difference-in-difference model) Formally, using geoprocessing tools, we have to:

$$light_{mst} = \sum_{i=0}^{63} \times (\#\ of\ pixels\ in\ municipality\ m, state\ s, and\ year\ t\ with\ DN = i) \quad (1.9)$$

On the other hand, when we take the analysis to the frontier, we use the value of each pixel for each year as an observation.

CO_2 Emissions

The data on CO_2 emissions were constructed from Global Greenhouse Gases Emission provided by the Emissions Database for Global Atmospheric Research (EDGAR). These data are digitally available from 1970 to 2012[41]. The EDGAR reports the CO_2 emission together with other gases for each place on the Earth with a resolution of 0.1° × 0.1° area pixel. Therefore, each pixel represents an area of approximately 123,5 square kilometers at the equator. Although annual CO_2 emissions data is available through 1970, we restring our sample to the year 2000 and 2010. CO_2 EDGAR data' are available in kilograms per square meter per second (Kg/m^2/sec). We convert these data in tons per square kilometers per year (tons/km^2/year) using the next equation:

$$CO_{2_{i,t_{\mathrm{tons/km2/year}}}} = CO_{2_{i,t_{\mathrm{Kg/m2/sec}}}} \left(\frac{1}{1000}\right)(1.000.000)(12.614.400)$$

where $CO2_{i,t_{\mathrm{tons/km2/year}}}$ represents the CO_2 average emission for the micro-region i and year t. The total annual emissions for each micro-region i is obtained from:

$$CO_{2_{i,t}} = CO_{2_{i,t_{\mathrm{tons/km2/year}}}} \left(Area_{i_{\mathrm{km2}}}\right)$$

where $CO_{2_{i,t}}$ represents the total annual emission of CO_2 for the micro-region i in the year t.

Population Data

We use population as a control variable. This dataset comes from the Gridded Population of the World (GPW), which is constructed by the Socioeconomic Data and

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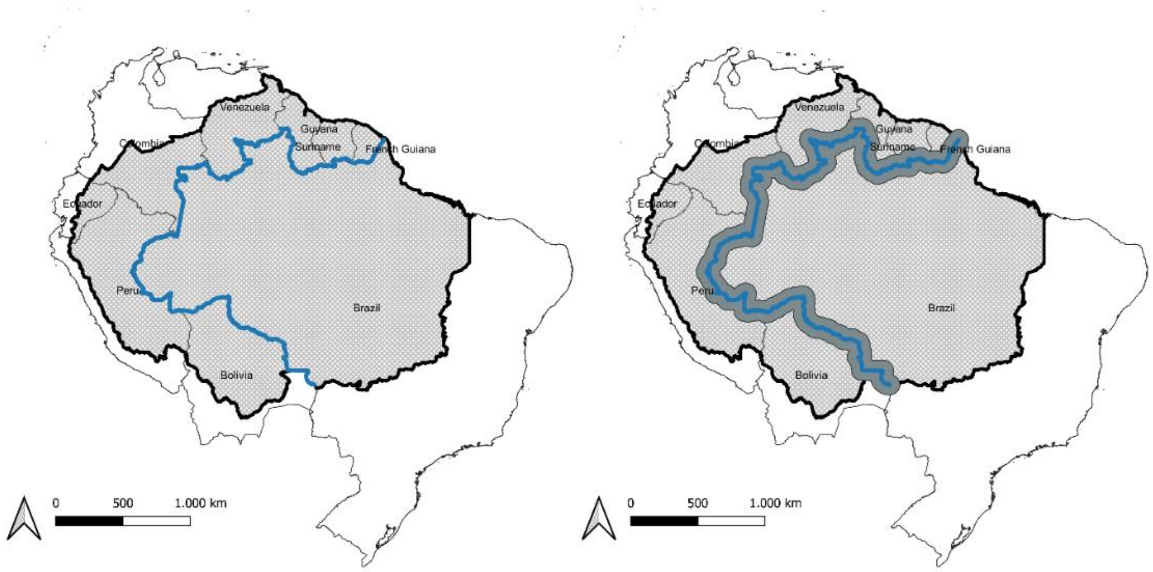
[41] Data about the EDGAR v.4.3.2, the most recent version, are available for download from the URL http://edgar.jrc.ec.europa.eu/overview.php?v=432_GHG&SECURE=123

Applications Center (SEDAC) at the Center for International Earth Science Information Network at the Earth Institute (CIESIN) at Columbia University. CIESIN provides information from national censuses corresponding to geographical boundaries.[42]

Geographic Limit Data

We use geographic data limits from different sources. The border Amazon area came from RAISG (*La Red Amazónica de Información Socioambiental Georeferenciada*). Shapefiles of limits of each country came from the DIVAS-GIS website.[43] Figure 1.2 displays the geographical area of analysis.

Figure 1.2: Amazon Legal - Geographic Limit



Note: The figure on the left represents the legal Amazon. In the figure on the left, we superimpose a 100 km buffer around the blue line, which represents the frontier.

Elevation and Slope Data

We also obtain controls for exogenous geographic characteristics. Elevation and slope data are from the Shuttle Radar Topography Mission (SRTM) provided by U.S.

[42] Data about the GPW version 4, the most recent, are available for download from the URL http://sedac.ciesin.columbia.edu/data/collection/gpw-v4/sets/browse

[43] Available at: https://pt.overleaf.com/project/5f6c9570adc48b0001d492e7

National Aeronautics and Space Agency. These data have the same resolution of Nighttime lights, 30 arc seconds.[44]

Temperature and Precipitation Data

We built a series for temperature and precipitation information using the ERA-Interim data produced by the European Center for Medium-Range Weather Forecasts (ECMWF). ERAInterin data are available at the 0:1 × 0:1 degree latitude/longitude grid. Given that these data are in a finer resolution than our main dependent variable, we will use raster calculator tools to match the spatial resolution of other data sources.

1.5. Descriptive Statistics and Results

1.5.1. Descriptive Statistics

Table 1.1 presents descriptive statistics for all the variables in our dataset at the municipality level. This data set is used in our first analysis. In particular, they are used in the estimates of the difference-in-differences model where the treated municipalities correspond to those found within the Brazilian legal Amazon and the control municipalities are all the rest. The sample is made up of 5287 municipalities, of which 772 belong to the legal Amazon (treatment group) and the remainder corresponds to the control group. We can observe that municipalities within the Brazilian Amazon have, on average, the highest amount of luminosity and the lowest CO_2 emissions. On the other hand, municipalities within the control group have higher levels of GDP, public spending, and a larger population. The Gini Index was lower for the municipalities of the treatment group.

[44] Version 2.1 (v2.1) are available for download from the URL https://webmap.ornl.gov/wcsdown/dataset.jsp?dg id=10008 1

Table 1.1: Descriptive Statistics at Municipality Level

	Observations	Mean	Standard Deviation
Treated			
Night Light	16842	2514.139	3693.498
CO_2 Emissions	16842	1.217522	5.157984
GDP	11244	241160.6	1458658
Public Spending	11937	4753529	22500000
Population	792	26586.53	81898.84
Gini	1597	.5783181	.0659201
Control			
Night Light	94185	1566.337	3580.741
CO_2 Emissions	94185	2.713222	18.55693
GDP	66490	476846.1	5578421
Public Spending	83265	6464849	6.03e+07
Population	4715	31546.69	199013.1
Gini	9470	.5202101	.0696504

Notes: Author elaboration.

1.5.2. Results

The results were divided in two subsections. On the one hand, we present the results from the difference-in-differece approach, which analyzed the effect of the PPCDAm on economic activity inside Brasil comparing municipalities belonging to Legal Amazon with municipalities outside before and after the PPCDAm implementation. In the other subsection, the effect of the PPCDAm came from a regression discontinuity approach. In this approach, we carried out the analyses at pixel level and compare pixels inside Brazilian territory with pixels just after the border before and after the implementation of the policy.

Difference in Difference Results

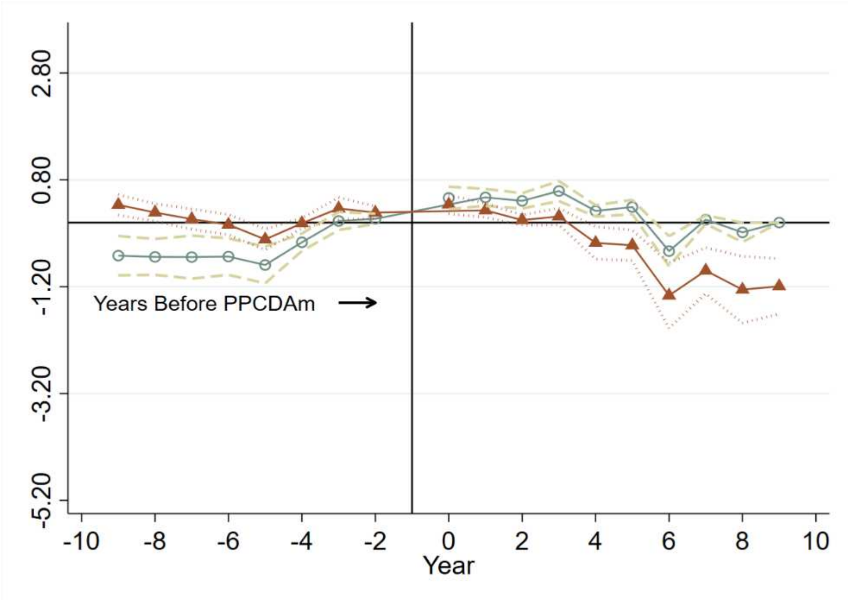
Event Study Analysis

We start our results by examining across an event study graph, the effect of the PPCDAm policy on the night light density in Brazilian municipalities. Figure 1.3 plots the estimated coefficients and their confidence intervals at 95 percent of significance from the dynamic specification (1.6). The series plotted with circles presents the results from a specification that includes only municipalities' fixed effects. The series with triangles plotted the specification that adjusts for municipality-specific linear trend and a set of socioeconomic characteristics interacted with a linear time trend. The dotted and dashed lines represent the respective 95 percent confidence intervals, where robust standard errors are clustered at the micro-region level. The omitted category is -1.

Examining the two specifications the results are similar, indicating a decrease in luminosity approximately from 4 years after the implementation of the PPCDAm. Exactly in 2008, when the second important action of the PPCDAm was implemented, the municipalities backlist. This result, to some extent, is contrary to the results found by Koch *et al.*, (2019) who do not find significant evidence in the reduction of agricultural production and the productivity in the beef, dairy, and crop production sector. However, these results should not be compared directly because Koch *et al.*, (2019) only evaluate the municipalities that are part of the blacklist compared to those that are not. In this analysis, on the other hand, we are considering all the municipalities of the legal Amazon compared to the rest of the municipalities of Brazil.

Figure 1.3 also shows that between 2004-2008 there is no statistical difference between treatment and control municipalities, suggesting that the PPCDAm may not have an immediate effect on policy enforcement. Furthermore, the graph also shows that there were no statistically significant differential trends in the night light intensity before the PPCDAm introduction, which provides strong support for the identifying assumption. Specifically, this assumption implies that municipalities that were exposed to the policy would have followed a similar trend in luminosity in the absence of the PPCDAm. This allows us to affirm that before the policy, the municipalities that belong and those that do not belong to the legal Amazon did not present differences in their trend of economic activity. Thus, the differences found after the 4th year of policy implementation can be attributed to the policy itself.

Figure 1.3: Impact of PPCDAm on Night Light Density



Note: This figure plots the event studies of the effects of PPCDAm on night light intensity. A series plotted with circles presents the results from a specification that includes only municipalities' fixed effects. The series with triangles plotted the specification that adjusts for municipality-specific linear trend and a set of socioeconomic characteristics interacted with a linear time trend. The dotted and dashed lines represent the respective 95 percent confidence intervals, where robust standard errors are clustered at the micro-region level. The omitted category is -1.

Main Results Diff-in-Diff

Table 1.2 shows the estimated coefficient of equation (1.5). Column (1) presents the results of the specification that have not adjustment. Results indicate that treated municipalities reduced the night light intensity. The coefficient is -0.67, which is statistically significant at the 1 percent level. In Columns (2) and (3), we add year and state fixed effect to the specification in Column (1), respectively. The results of these specifications change slightly. Column (4), our preferred estimate, includes year fixed effect, state fixed effect, municipality-specific trend, and the interaction between the population in 2000 with a time linear trend. The standard error is clustered at the Mesoregion level for accounting for spatial correlation. In Column (5), we include sociodemographic controls (population, GDP and public spending). We can observe that the estimated coefficient does not have significant changes through the different specifications (went from -0.67 in column (1) to -0.60 in column (4)), which indicates robustness in the estimation.[45] The estimated coefficient is -0.60 (standard error=0.112) and is statistically significant at the 1 percent level. Taken this together,

[45] As can be seen, the number of observations in column 5 decreases once these sociodemographic variables are not available for all the years analyzed.

there is a statistically decrease in the light night intensity after the PPCDAm implementation. This evidence is consistent with the graphical result.

Taking into account our hypothesis that if the PPCDAm policy has effects on deforestation, consequently it could have effects on economic activities directly or indirectly related to deforestation. There is evidence that deforestation reduces rainfall and consequently reduces income from agriculture in the Brazilian Amazon (LEITE-FILHO *et al.*, 2021). Our results are consistent with the literature that analyzes the effects of PPCDAm on deforestation. Hargrave and Kis-Katos (2013), for example, using data panel of 663 municipalities from 2002 to 2009, estimate the monitoring and law enforcement policy on deforestation. The authors find that deforestation in the Amazon biome increase with the economic activity, and is affected by fluctuation in agricultural products and wood prices. They also provide evidence that municipalities with high-level intensity in law enforcement present a significant reduction in deforestation rates. These results are also consistent with Assunção, Gandour, and Rocha (2015), who find that conservation policy affects deforestation after controlling for agricultural prices effects. Using a municipality-by-year data panel between 2002 and 2009, the authors show that the policy helped to reduce deforestation by 73000 km^2.[46] More specifically, total deforestation in the period 2004-2008 was 57,000 km^2, 56 percent smaller than the 130,000 km^2 estimated in the absence of the intervention (ASSUNÇÃO; GANDOUR; ROCHA, 2015). More recently, Burgess, Costa, and Olken (2018), exploiting the Brazilian national border to estimate the policy effect, find that the deforestation rates in the Brazilian area were relatively similar to its neighborhood after 2006 - just after the policy was implemented. Before the PPCDAm implementation, the annual deforestation in Brazilian land was more than three times higher than its neighbor countries (BURGESS; COSTA; OLKEN, 2018). Thus, command and control policy - federal government presence and effective enforcement of the law - is successful in reducing deforestation in the remotest part of Brazilian territory, almost in a short time.

The results are also in line with recent studies that analyze the policy effects of priority municipalities, like Arima *et al.*, (2014), who based on the estimation of

[46] Assunção, Gandour and Rocha (2015) take advantage of a municipality panel data from 2002 to 2009 to evaluate empirically the effectiveness of Amazon conservation policy. In particular, they estimate a regression model and control by municipality and year fixed effects, and municipality-specific time trends.

difference-in-difference and matching estimators, documented a significant reduction in deforestation in municipalities with “priority status”. In particular, they found that the Priorities Municipalities policy has avoided deforestation up to 10653 km^2 in blacklisted municipalities over the period from 2009 to 2011. In the same vein, Assunção and Rocha (2019), analyzing MP’s policy, also find that belonging to the blacklist avoided the deforestation of 11,359 km^2 of Amazon Forest between 2008 and 2011. More specifically, the authors show that, between 2008 and 2011, deforestation was 20689 km^2, which represents a slowdown of 35 percent if we compare it with a situation of absence of the policy (ASSUNÇÃO; ROCHA, 2019). They also analyze the impact of MP’s policy on agricultural GDP, crop production, and rural credit, finding that the policy does not affect these variables. However, when they analyze the effect on environmental fines, they find a significant effect. An interesting finding of these authors is that when adequately controlled by law enforcement, this intervention does not present significant effects on deforestation.

Cisneros, Zhou, and Börner (2015), in contrast to these results, implementing a double difference estimator combining with spatial matching techniques, show that the municipalities that belong to the blacklist have experiment higher reduction on the deforestation than non-blacklisted municipalities even after controlling for the mechanism of enforcement law, environmental registration campaigns, and rural credit. Assunção *et al.*, (2019) corroborated these results. The authors use a novel estimation approach of changes-in-changes and provide evidence of a reduction in deforestation of 40% in a short period (2009-2010) in priority compared with non-priority municipalities. Specifically, Assunção *et al.*, (2019) estimated a total reduction of 3323 km^2 of preserve forest in target municipalities, 2705 km^2 that correspond to the direct priority municipalities, and 618 km^2 corresponding to spillover effects. Andrade (2016) also finds spillover effects in neighboring untreated municipalities. Using a spatial difference-in-difference approach, to take into account potential spatial autocorrelation biases, Andrade (2016) estimates that the net effect of the blacklist on non-blacklist neighbors is an average decrease in deforestation between 19% and 23%. They also documented that this effect decreases as the distance to the listed municipality increases.

Table 1.2: The effect of PPCDAm on Night Light Intensity

Policy	-0.678***	-0.678***	-0.603**	-0.603***	-0.248**
	[0.058]	[0.190]	[0.225]	[0.112]	[0.112]
Observations	122342	122342	122342	122342	62377
R-squared	0.021	0.968	0.968	0.968	0.982
Year Fixed Effects	NO	YES	YES	YES	YES
Municipality Fixed Effects	NO	YES	YES	YES	YES
Municipality-Specific trends	NO	NO	YES	YES	YES
Time trends interacted with:					
Population	NO	NO	NO	NO	YES
GDP	NO	NO	NO	NO	YES
Public Spending	NO	NO	NO	NO	YES

Source: Research results.
Notes: annual average light intensity in municipality m, state s and, year t.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Other Related Outcomes

We now turn to an examination of possible related outcomes that the PPCDAm can affect. In particular, we use the CO_2 emissions as dependent variable.We hypothesize that the policy reduces deforestation and consequently reduce the CO_2 emissions. Since various economic activities produce CO_2 emissions, one would expect that the reduction of CO2 is associated with a reduction in economic activity and as a consequence the luminosity could be diminished. We emphasize, although this exercise does not allow us to make causal claims about this relationship, that the statistical relationship is strong and significant.

To shed light on this hypothesis, we examine the effect of the PPCDAm on a set of economic and environmental outcomes potentially associated with the night lights density. First, we use information about CO_2 emission and estimate simple OLS regression to know the relationship with the gross domestic product at the municipal level. Table 1.3 and Figure 1.4 summarize the results of this exercise. Figure 1.4 provides evidence of the strong correlation between CO_2 Emission and Night Light Intensity especially from 2003. Table 1.3 presents the results of OLS estimation where the dependent variable is the log of CO_2 emissions in tons per year while the independent variable is the log of mean of the nighttime lights. Each coefficient is from a different regression. Column (1) is based on an OLS estimation that does not have any adjustment. Column (2), in turn, adds municipality and time-fixed effects to the specification from column (1). In column (3), we add municipal-specific trends. Finally, in Columns (2)-(4) we estimate robust standard errors (reported in brackets) are clustered at microregion level. We found a strong and positive correlation between CO_2 emission and night light. The estimated coefficient in column (4) suggests that an increase in 1% in the CO_2 emission is associated with an increase in 0.1 points percent in the night light density.[47] This results is in line with OU *et al.* (2015) who show that night lights data can be useful tool to study the spatial distribution of CO_2 emissions.

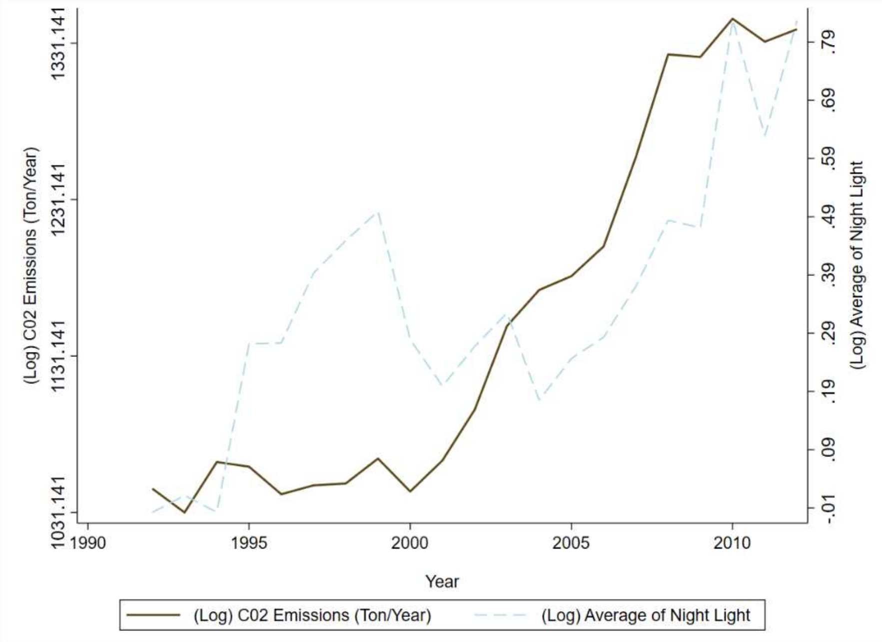
Table 1.3: Relationship CO_2 Emissions and Night Lights Intensity

CO_2 Emission (in log)	0.368***	0.065**	0.109***	0.109***
	[0.002]	[0.028]	[0.030]	[0.013]
Observations	111027	111027	111027	111027
R-squared	0.226	0.956	0.957	0.957
Year Fixed Effects	NO	YES	YES	YES
Municipality Fixed Effects	NO	YES	YES	YES
Municipality-Specific trends	NO	NO	YES	YES

Notes: The dependent variable is the log of CO_2 emissions in tons per year while the independent variable is the log of the mean of the nighttime lights. Each coefficient is from a different regression. Column (1) is based on an OLS estimation that does not have any adjustment. Column (2), in turn, adds municipality and time-fixed effects to the specification from column (1). In column (3), we add municipal-specific trends. Finally, in Columns (2)-(4) we estimate robust standard errors (reported in brackets) are clustered at microregion level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

[47] There is a long literature that has used luminosity data as an alternative to carbon dioxide emissions data due to its high resolution compared to various carbon dioxide measurements, see for example Ou *et al.*, (2015) for a detailed review.

Figure 1.4: CO_2 Emissions (Tons/Year) and Night Lights Intensity Trend (1992-2012)



Notes: The solid line represents the trends of the logarithm of the total annual CO_2 emissions in tons while the dashed line plots the logarithm of the average of night lights intensity in Brazil between 1992 and 2012. Author's elaboration from data of the Emissions Database for Global Atmospheric Research (EDGAR) and National Oceanic and Atmospheric Administration's. (NOAA).

Now, we estimated Equation 1.7 using CO_2 Emissions as the dependent variable which allows us to examine how the CO_2 emission is affected by the PPCDAm.[48] Table 1.4 displays the results of this exercise. We find that the PPCDAm reduce significantly the municipalities' CO_2 emissions. One may think that this decrease in CO_2 emissions are associated with the decrease in deforestation. This result is in line with Rochedo *et al.*, (2018) who document that greenhouse gas emission in Brazil decreased by about 54% between 2005 and 2012, mainly due to the 78% reduction in deforestation. Taking this together, we can expect that a decrease in CO_2 emissions could decrease the luminosity.

[48] Deforestation is considered the second largest source of greenhouse gas emissions, losing only to the burning of fossil fuels (VAN DER WERF *et al.*, 2009). It is estimated that approximately 6 to 17 percent of anthropogenic CO_2 emissions to the atmosphere come from tropical deforestation (BACCINI *et al.*, 2012).

Table 1.4: The effect of PPCDAm on CO_2 emissions

Policy	-0.086***	-0.086***	-0.026	-0.026***
	[0.022]	[0.018]	[0.018]	[0.004]
Observations	111027	111027	111027	111027
R-squared	0.026	0.494	0.494	0.494
Year Fixed Effects	NO	YES	YES	YES
Municipality Fixed Effects	NO	YES	YES	YES
Municipality-Specific trends	NO	NO	YES	YES

Source: Research results.
Notes: annual average light intensity in municipality m, state s and, year t.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

RDD Estimation Results

Main Results

In this subsection, we carried out the analysis in a context similar to Burgess, Costa, and Olken (2018). We estimate a regression discontinuity design to estimate the power of Brazilian institutions. In particular, we estimate the local average PPCDAm policy effect at the Brazilian border on the night light density and the growth rate of the night light density. As we mentioned in the empirical strategy section, we compare areas inside Brazilian territory with areas outside Brazil in countries where Brazil shares the frontier inside the Legal Amazon Forest.

Table 1.6 shows the estimated coefficients of Equation 1.8 considering the raw value of light intensity. Each column represents a specific year estimation. In panel a, we carried out the estimation considering a bandwidth of 1 kilometer, while panels b, c, and d the estimation considering bandwidths for 5, 25, and 100 kilometers, respectively. We observe that considering bandwidth of 1 and 5 kilometers, there is no statistical difference between the night light density between Brazil and their neighborhoods. Using a 25 km bandwidth from the border, we find that nighttime luminosity intensity is greater within Brazil than in its neighboring counterpart both before and after the policy. This result seems to indicate that the deforestation reduction policy does not affect luminosity, at least in an area 25 km from the border. However, when we consider 100 kilometers of bandwidth from the border, we found that the intensity of night lights appears to be lower within Brazil compared to its neighbors before politics and the first 3 years of politics. However, for 2008, 2011, 2012, and 2013 we did not find statistical differences. This result is, in part, in line with Burgess, Costa, and Olken (2018) who found that before the policy implementation areas inside Brazil were experiencing greater deforestation than areas in neighboring countries and after the policy, these differences disappeared.

Now we estimate Equation 1.8, but now we use the growth rate of the night lights as an outcome variable instead of the intensity in its raw value. Table 1.7 summarizes the main results of this exercise. The results are similar to those found previously using the raw values of the luminosity, especially when we consider the bandwidth of 1 and 5 kilometers. In particular, we found that there is no difference between pixels inside Brazil and pixels just across the border outside of Brazil, which can be understood as no differences in the growth rates of economic activity between countries if we consider just one side of the border and the other. Focusing on panel c, we consider a bandwidth of 25 kilometers. The estimated coefficient reveals that in 2004 the intensity growth rate in night lights was higher in pixels within Brazil, but in the following year (the year the policy was implemented) the estimated coefficient became negative, suggesting a decrease in economic activity within Brazil. For 2006, this difference became negative, although not significant. Figure 1.5 plots this result.[49] This result suggests that as we consider a higher bandwidth, that is, we take more distant pixels from the border, the policy seems to have effects on economic activity. This can be explained because as we distance ourselves from the border, access to areas with potential for deforestation may be greater, which would facilitate the application of the law compared to more remote areas.

[49] Figures A.1 - A.2 in appendix A display the RDD plots using different bandwidth choices.

Table 1.6: Impact of PPCDAm on Night Lights Density 2000-2013

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
	Bandwidth 1 Kilometer													
Policy	-0.0765	-0.0648	-0.0591	-0.0874	-0.0707	-0.102*	-0.102	-0.106	-0.0996	-0.0889	-0.114	-0.0885	-0.122	-0.112
	(0.0627)	(0.0644)	(0.0628)	(0.0622)	(0.0678)	(0.0600)	(0.0726)	(0.0786)	(0.0761)	(0.0745)	(0.0946)	(0.0875)	(0.0943)	(0.0930)
	Bandwidth 5 Kilometers													
Policy	0.00180	0.00344	0.0129	-0.00679	0.0149	-0.0182	-0.0163	-0.00880	0.0108	-0.00404	-0.00782	0.0310	-0.00188	0.0121
	(0.0252)	(0.0263)	(0.0248)	(0.0242)	(0.0268)	(0.0240)	(0.0298)	(0.0319)	(0.0309)	(0.0302)	(0.0390)	(0.0361)	(0.0393)	(0.0386)
	Bandwidth 25 Kilometers													
Policy	0.0388***	0.0393***	0.0548***	0.0306***	0.0577***	0.0337***	0.0416***	0.0496***	0.0576***	0.0458***	0.0488***	0.0876***	0.0764***	0.0832***
	(0.00880)	(0.00912)	(0.00885)	(0.00814)	(0.00937)	(0.00849)	(0.0105)	(0.0112)	(0.0109)	(0.0105)	(0.0140)	(0.0130)	(0.0142)	(0.0139)
	Bandwidth 100 Kilometers													
Policy	-0.0119***	-0.0109***	-0.00451	-0.00840***	-0.00370	-0.00961***	-0.00907**	-0.00720*	-0.00357	-0.00797**	-0.0202***	4.25e-05	-0.00589	-0.000275
	(0.00308)	(0.00315)	(0.00315)	(0.00278)	(0.00327)	(0.00297)	(0.00366)	(0.00385)	(0.00376)	(0.00363)	(0.00496)	(0.00454)	(0.00496)	(0.00483)
Observations	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610	1.742.610
Covariates	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

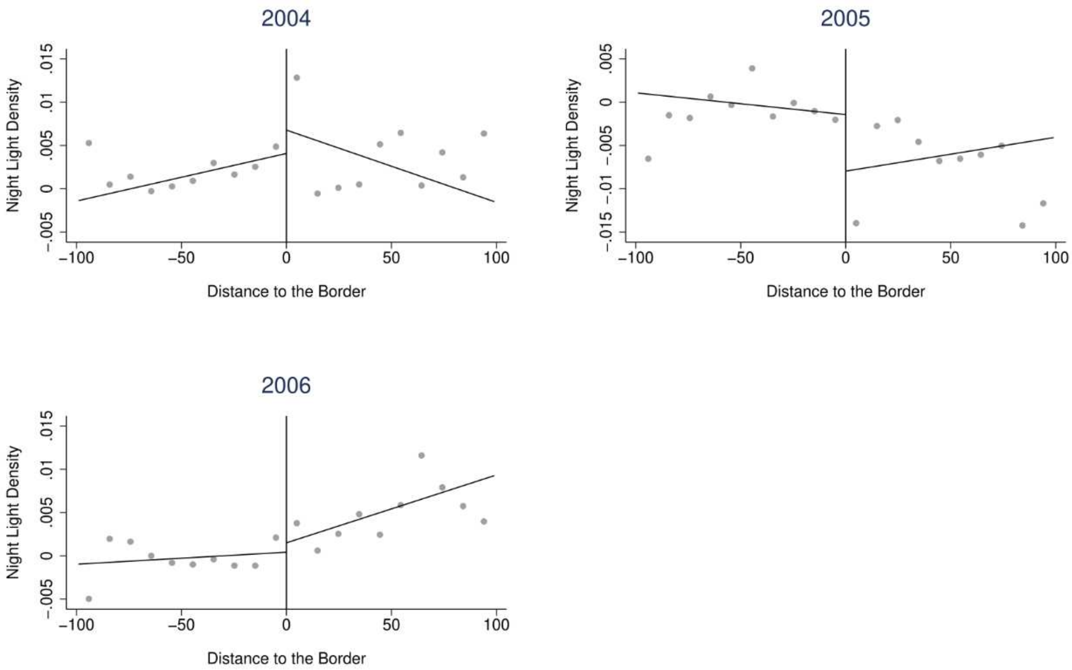
Note: This table summarizes the estimated coefficients from Equation 1.8, which estimates the effects of PPCDAm Brazilian policy on economic activity. The estimation was carried out with linear polynomials and triangular kernels. Each panel shows the estimated coefficient using a specific bandwidth (1, 5, 25, and 100 kilometers, respectively)

Table 1.7: Impact of PPCDAm on Night Lights Growth Rates 2001-2013

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
	Bandwidth 1 Kilometer												
Policy	-0.00431	0.0194	-0.0180	0.0136	-0.0200	0.0134	0.00362	-0.00151	0.0214	-0.0271*	0.00408	0.00360	-0.00423
	(0.0128)	(0.0159)	(0.0149)	(0.0133)	(0.0174)	(0.0161)	(0.0126)	(0.0136)	(0.0156)	(0.0154)	(0.0215)	(0.0167)	(0.0127)
	Bandwidth 5 Kilometers												
Policy	-0.00621	0.00843	-0.0135*	0.0116*	-0.00761	0.00218	-0.00152	0.00391	0.00722	-0.00748	-0.00159	-0.00365	-0.00492
	(0.00626)	(0.00707)	(0.00766)	(0.00682)	(0.00796)	(0.00719)	(0.00714)	(0.00713)	(0.00687)	(0.00815)	(0.00960)	(0.00794)	(0.00612)
	Bandwidth 25 Kilometers												
Policy	-0.00867***	0.0106***	-0.00537*	0.00875***	-0.0132***	0.000543	0.00672**	0.00353	-0.00286	0.00452	0.0118***	-0.00538	0.00531*
	(0.00287)	(0.00320)	(0.00325)	(0.00300)	(0.00362)	(0.00314)	(0.00329)	(0.00337)	(0.00318)	(0.00395)	(0.00434)	(0.00377)	(0.00304)
	Bandwidth 100 Kilometers												
Policy	-0.00321**	0.00657***	-0.00418***	0.00555***	-0.00962***	0.000428	0.00351**	0.00230	-0.00107	-0.00431**	0.00763***	0.000501	0.00189
	(0.00126)	(0.00141)	(0.00141)	(0.00137)	(0.00172)	(0.00140)	(0.00148)	(0.00151)	(0.00150)	(0.00189)	(0.00196)	(0.00177)	(0.00151)
Observations	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900	1.697.900
Covariates	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: This table summarizes the estimated coefficients from Equation 1.8, which estimates the effects of PPCDAm Brazilian policy on annual average night light growth rate from 2000 to 2013. The estimation was carried out with linear polynomials and triangular kernels. Each panel shows the estimated coefficient using a specific bandwidth (1, 5, 25, and 100 kilometers, respectively)

Figure 1.5: Impact of PPCDAm on Night Light Density



Note: This figure presents the local average treatment effects from the estimation of Equation 1.8 of PPCDAm policy on night light growth rate. The running variable is the distance to the border. The estimation was carried out with Kernel triangular and the bandwidth is 100 kilometers. For this figure, we use 10 bins.

1.6. Conclusion

During the decade 2000, the Brazilian government launched a set of political actions to control the forest clearing in the Amazon region. In this chapter, we assess the effectiveness of the PPCDAm policy on economic activity. In doing so, we use high-resolution satellite data on night light intensity as a proxy for economic activity over 2000 - 2013. We implement several empirical strategies to better estimate the causal effect of policy on economic activity. In particular, we use the difference in difference and regression discontinuity design estimations. The results indicate that the PPCDAm reduces the economic activity in municipalities treated by the policy compared with non-treated only in the fourth year after the policy was implemented. Alternatively, when we move the analysis to the Brazilian frontier, taking pixels within the Brazilian territory and comparing them with pixels outside of Brazil, we find that at bandwidths of 1 and 5 kilometers there is no statistical difference in the density of light. Nevertheless, using a 25 kilometers bandwidth, we found that before the policy the growth rate of luminosity in the Brazilian territory was relatively higher than that of its neighbors. One year after the implementation of the policy, the growth rate became negative and subsequently became statistically insignificant. Collectively, these findings suggest that the PPCDAm policy affects economic activity.

The negative effect on economic activity is difficult to conciliate with previous studies that find no effects of PPCDAm on economic activity measure using traditional GDP (Koch et al., 2019). However, it seems plausible to think that if much of the deforestation activity is illegal, the economic results of this entire process are not reported in traditional measures of economic activity. Rather, our findings are consistent with the theory of tradeoff between environmental protection and economic output.

We also investigated other related outcomes that the implementation of the policy can affect and consequently affect the luminosity. In particular, we use data on CO_2 emission and we show that the PPCDAm reduced the CO_2 emission in the municipalities treated by the policy. The data in this study do not allow us to differentiate whether the years where we do not find a difference in treatment areas and control areas the PPCDAm had an effect or not. There may be a decrease in economic activity resulting from the decrease in illegal deforestation (the policy affecting its main purpose), but there may be a substitution effect of illegal deforestation activities for other types of productive activities. Our results can provide useful information to public policy makers once the protection policies can be implemented in a conscious way without drastically affecting the economic activities developed in the regulated areas. One of the great discussions in the application of environmental protection policies is that it economically affects the populations that benefit from the exploitation of the environment. In the particular case of the PPCDAm, once deforestation is prohibited in specific areas, the economic agents that benefit from deforestation could be financially affected. However, our results reveal that economic activity in regulated areas is not drastically reduced, which may be reassuring for those economic agents involved in new environmental regulation policies.

Future research can carry out this analysis identifying if there is a substitution of illegal deforestation by other types of productive activities. This may provide important insights for possible complementary policy. Furthermore, a limitation of our work is that there may be a change in economic activity and productivity in less regulated areas, which could generate biased estimates. Future works could consider the incorporation of these potential spillover effects.

Appendix A

Table A.1: The effect of PPCDAm on Night Light Intensity

Policy	-0.678***	-0.678***	-0.678***	-0.678***	-0.447***
	[0.058]	[0.118]	[0.118]	[0.058]	[0.063]
Observations	122342	122342	122342	122342	62377
R-squared	0.021	0.670	0.676	0.676	0.735
Year Fixed Effects	NO	YES	YES	YES	YES
Municipality Fixed Effects	NO	YES	YES	YES	YES
Municipality-Specific trends	NO	NO	YES	YES	YES
Time trends interacted with:					
Population	NO	NO	NO	NO	YES
GDP	NO	NO	NO	NO	YES
Public Spending	NO	NO	NO	NO	YES

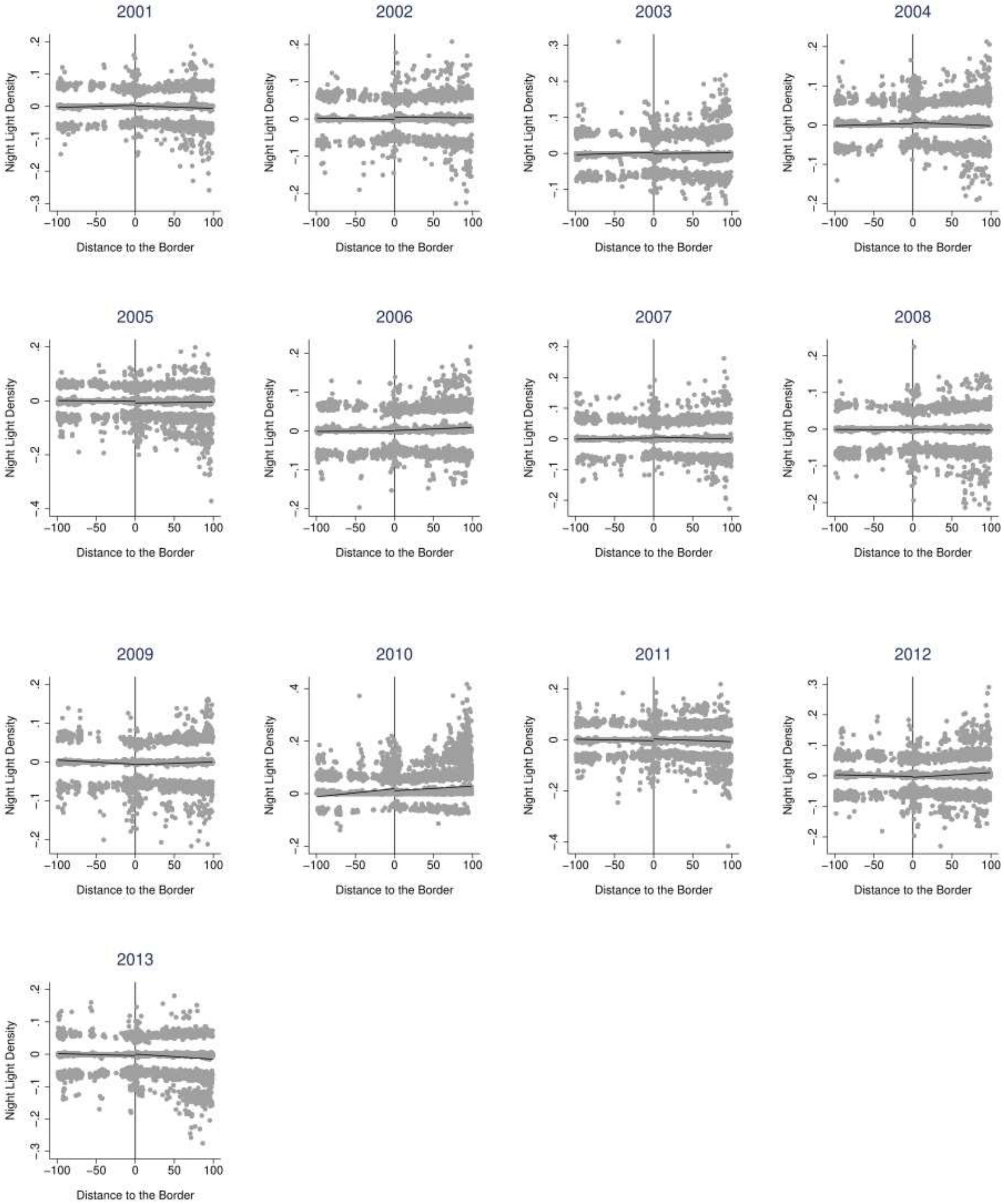
Source: Research results.
Notes: annual average light intensity in municipality m, state s and, year t.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A.2: The effect of PPCDAm on Night Light Intensity

Policy	-0.009***	-0.009***	-0.009***	-0.009***	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	122342	122342	122342	122342	62377
R-squared	0.021	0.670	0.676	0.676	0.735
Year Fixed Effects	NO	YES	YES	YES	YES
Municipality Fixed Effects	NO	YES	YES	YES	YES
Municipality-Specific trends	NO	NO	YES	YES	YES
Time trends interacted with:					
Population	NO	NO	NO	NO	YES
GDP	NO	NO	NO	NO	YES
Public Spending	NO	NO	NO	NO	YES

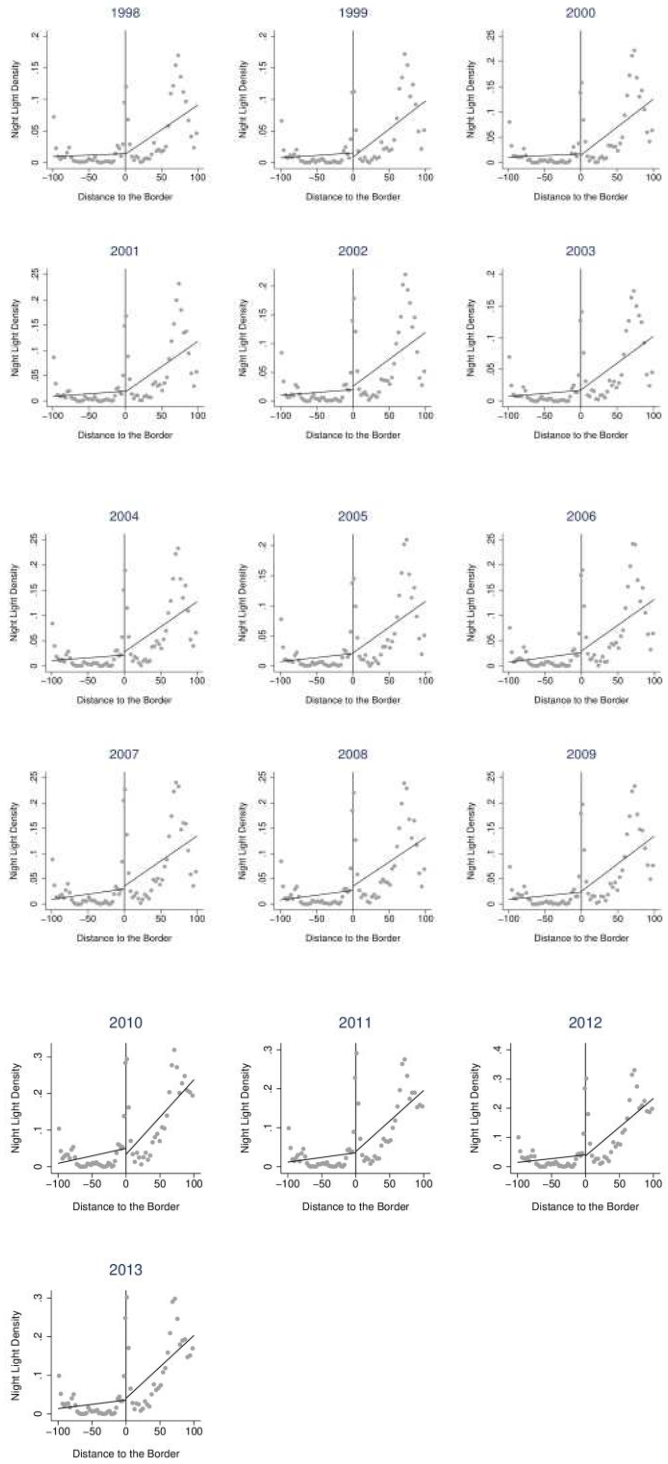
Source: Research results.
Notes: annual average light intensity in municipality m, state s and, year t.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A.1: RDD Plots Distance to the Border 100KM Polynomial Level 1



Notes: This figure displays the annual average night light growth rate from 2000 - 2013. The coefficient point estimated proceeds from Equation 1.8 using a triangular kernel function, a polynomial level one and, a bandwidth of 100 kilometers.

Figure A.2: RDD Plots Distance to the Border 100KM polynomial Level 1



Notes: This figure plots the annual average night light density for each year between 1992 - 2013. The bandwidth is 100 kilometers. The local polygonal is level one and the number of bins was chosen across the Integrated Mean Squared Error (IMSE) optimal number.

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Chapter 2
Road Infrastructure and Local Economic Activity in Brazil

Abstract

Road infrastructure brings significant economic benefits essential for economic development and growth. This chapter examines the long term effect of a road infrastructure project carried out in Brazil from the decade 60's on the economic activity in Brazil. We use the creation of Brasilia as a natural experiment in order to estimate the causal effect of road investment on economic activity (measuared as a night light density) at the microregion level. Our results reveal that microregions located near to the highway corridor showed higher luminosity in 1992-2012 than microregions located far away.

JEL codes: O10; O18; R12

Keywords: Nighttime Light. Infraestructure. Regional Economics.

2.1. Introduction

Providing public goods has been an important role of governments in order to stimulate economic activity and improve the population welfare. Several studies have demonstrated that the provision of transport infrastructure has a positive effect on economic activity through the increase of productivity and reduction in transportation costs (CALDERÓN; SERVÉN, 2014). Roads, for instance, bring significant economic benefits essential for economic development and growth. The creation of roads not only improves the connection between regions but also roads can open this region to trade and investment, as well as increase employment opportunities and access to goods and services. The idea behind this hypothesis is that one needs to have access to the market for obtaining benefits from it (BANERJEE; DUFLO; QIAN, 2012; DONALDSON; HORNBECK, 2016).

There is empirical evidence for the United States (CHANDRA; THOMPSON, 2000; BAUM-SNOW, 2007; MICHAELS, 2008), India (DATTA, 2012; GHANI;

GOSWAMI; KERR, 2016; ALDER; ROBERTS; TEWARI, 2017), China (BANERJEE; DUFLO; QIAN, 2012; FABER, 2014; BAUM-SNOW *et al.*, 2015) showing how road infrastructure stimulates economic growth. In Brazil, several papers have been studying the effects of road infrastructure on economic output at national level (BIRD; STRAUB, 2020; DIAS, 2021), however, there is considerable less research on the effects and persistence at subnational level. Given the importance of the transport infrastructure improvement in the economic activity, it seems attractive to analyze the Brazilian case.

In this essay, we study this issue by examining the persistence of public investment in infrastructure – measure as the construction of roads network – done from the 1960s in Brazil on the local economic activity – measure as the night-light's density. This period provides an exceptional opportunity to study public investment in many ways. During this period, Brazil engaged in huge infrastructure projects – mainly in the construction of several road networks – that had the objective to connect the new capital recently created – Brasilia – with the other main population and economic centers of the country (BIRD; STRAUB, 2020).[50] According to the World Bank (2008), 150.000 kilometers of road were created in this period, which is approximately 9% of 1.75 million kilometers of Brazilian highway in 2012 (WORLD BANK, 2012), which made this scenario very attractive.

We hypothesize that Brazilian transportation infrastructure plays a vital role in long-run economic output through access to the market (DONALDSON; HORNBECK, 2016), improvement in the productivity and agglomeration economies. Testing this hypothesis is a challenging task. Transport infrastructure projects are often non-randomly distributed across places (DONALDSON, 2018). Indeed, they are usually allocated by endogenous economic or political factors. They are allocated according to observable and unobservable characteristics, which make it difficult to identify the causal effect due to the potential correlation between these characteristics and the economic activity. Governments might allocate new infrastructure projects in areas with a high potential economic growth in order to take advantage of its positive path of prosperity. We can observe that the richest regions have more and better road

[50]Although the Brazilian road network is the fourth largest in the world, in 2015 Brazil was ranked 120th out of 140 countries in road quality according to an index calculated by the World Economic Forum (WORLD ECONOMIC FORUM, 2015).

infrastructure, and this stimulates the economic growth of the region as well as the construction of new roads, and so on.[51] By contrast, the government might invest in the poorest areas or areas with a lower potential for growth in order to encourage it in a path of growth. Taken together, a potential solution for the problem of endogeneity of placement of road infrastructure could be the random assignment of infrastructure projects, which seems less plausible.

Several papers try to deal with this endogeneity problem by exploiting natural experiments (DONALDSON, 2018). Nevertheless, finding natural experiments that allow impact evaluations in this context are rare and uncommon.[52] Under this limitation, various studies have implemented identification strategies to mimic controlled random experiments; instrumental variable (BANERJEE; DUFLO; QIAN, 2012; CHANDRA; THOMPSON, 2000), the difference in difference (DATTA, 2012) and, the difference in difference with instrumental variable (FABER, 2014). Our identification strategy tries to overcome this challenge by taking advantage of the creation of a new Brazilian federal capital city –Brasilia–, which could be considered as a natural experiment. After Brasilia's creation, several road networks were constructed with the objective to connect the isolated capital with the main economic centers (BIRD; STRAUB, 2020). The new interstate highways achieved some intermediate areas through the way that were not endogenously chosen. Therefore, the distance (closer or farther) between intermediate areas and the new highway could be considered exogenous and orthogonal with the area’s characteristics. We compare areas located 0-10 kilometers from the highway to areas 10-50 kilometers away in order to capture the effect of the highway.[53] We might think that highway constructions affected differently the economic activity of those areas close to the highway relative to areas farther away, and if they had experienced a high provision of road density in the past, they might have more density today.

Our findings suggest that microregions closer to any of eight roads display higher night light intensity than microregions far away. The main results are robust to different econometric specifications and different clusters. The results are similar when

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[51] Thus, the simultaneity present in these two variables can confound the true effect.
[52] Donaldson (2018), Chandra and Thompson (2000) are exceptions.
[53] The distance was chosen arbitrarily. We test different distances in order to validate the sensibility of our estimation.

we use different specifications of the dependent variable as well as when we use alternative measures of the proximity to the highways.[54]

Next, we investigate the underlying mechanism by which this relationship is given. We estimated our main specification using the number of economic establishment as an outcome variable instead of the measures of night light intensity. The estimates indicate a strong influence of the road infrastructure on the allocation of the establishment. Specifically, our results suggest that microregions located near the highways present a higher number of economic establishment relative to microregions located further from the roads. These results are useful to policy implications. Policymakers should consider understanding how road projects influence the spatial distribution of economic activity at a disaggregate level.

This chapter contributes to a large literature on the estimation of the economic effects of infrastructure projects. For example, Duflo and Pande (2007) estimate the effects of dam construction on agricultural productivity in India. Lipscomb, Mobarak, and Barham (2013) evaluate the effects of hydropower plants construction on labor productivity in Brazil. Dinkelman (2011), in its turn, analyzes the impact of electrification on employment growth in South Africa.

We also contribute to ongoing literature that examines the persistence of the effects of the road or railroad public investment on economic outcomes. Atack *et al.*, (2010), for example, show that access to the railroad in the American Midwest had positive and strong effects on the rate of urbanization but its effect on population growth is small. Donaldson (2018), using archival data sources from colonial India to estimate the impact of railroad networks on interregional and international trade, finds an increase in interregional and international trade with a decrease in trade cost. Our study is more closely related to Jedwab and Moradi (2016), Jedwab, Kerby, and Moradi (2017), and Banerjee, Duflo, and Qian (2012). Jedwab and Moradi (2016) and Jedwab, Kerby, and Moradi (2017) analyze the formation of African cities along Colonial and show that the cities formed during the colonial period persist until today. Similarly, but in a different setting, Banerjee, Duflo, and Qian (2012) estimate the effects of access

[54] The use of night light density in this context as a proxy for economic activity could present some limitations due to the fact that road infrastructure may bring electricity to the regions connected for the new highways producing more luminosity at night. However, we understand that the arrival of electricity to these regions is the product of the increase in economic activity associated with the construction of highways and not the opposite.

to transportation networks on regional outcomes in China. They find that the proximity to transport networks has a positive effect on per capita GDP across sectors but no effects on GDP growth.

Although some papers have studied the effects of shocks of highways construction on goods and labor markets (MORTEN; OLIVEIRA, 2016), urban population, and GDP per capita (GRIMES; MATLABA; POOT, 2017) in Brazil, we are not aware of any work that evaluates the long term effects of the construction of road infrastructure using the night-light density as a proxy of economic activity. This chapter contributes to this literature by providing more accurate estimations of the effects of transportation infrastructure on economic activity at local level. Therefore, it is important for policymakers to understand the return on investment in the long run of transport infrastructure projects at disaggregated level.

The remainder of the paper is organized as follows. Section II summarizes the background of the road system in Brazil. Section III presents the theoretical framework. Section IV provides the data sources and detailed information of descriptive statistics of the data. Section V introduces the empirical strategy. Section VI contains the main results and discussion, and section VII concludes.

2.2. Background

Infrastructure plays an important role in the economic activity of any nation (DONALDSON; HORNBECK, 2016). The world road system is conformed by 1,75 million km, of which only 12.4% (213,453 km) is paved, 78.5% are not paved and 9.1% are planned. Brazil has the fourth-largest road infrastructure network in the world. However, the Brazilian road network seems to be insufficient for the demands of the economy. The road transport system represents the largest participation in the transport matrix, moving about 61% of freight and 95% of the passengers. Although these conditions make the road system look deficient, this is a significant contributor to the logistics system for most firms operating in the country.[55]

[55] In order to improve this situation, investment in infrastructure has become a policy priority. Recently, in the second mandate of President Lula, the Brazilian government launch the *Programa de Aceleração de Crescimento* (PAC by its acronym in Portuguese) with the focus to improve the infrastructure in several economic sectors including logistics, energy, social and, urban (Stanley, 2010). With all this public investment, these levels continue to be low compared to the levels recorded in the 1960s when

The development of the road system dates back to the 1950s. Before the 1950s, the highways in Brazil were mainly concentrated in the coastal areas of the Northeast and Southeast regions. The road system was composed of around 49000 km in length, while the railroad network was around 30000 km (World Bank, 2008). Nevertheless, some important events in this decade changed the country's road infrastructure. In particular, the creation of the new Brazilian capital, Brasilia.

Brasilia was constructed from scratch between 1956 and 1961. The idea to move the Brazilian capital from Rio de Janeiro to a centralized place in order to develop the central regions, to integrate the central-west and northtern region and explore the natural resources present in this area date back to 1789 (GRIMES; MATLABA; POOT, 2017). This initiative was entered into the Brazilian constitution in 1891 but only was carried out under President Juscelino Kubitschek. The new capital began to be built in 1956 and, 3 years and 10 months later, it was officially inaugurated on April 21, 1960. Together with the new federal capital city, the Brazilian government started to construct several highways that have the objective to connect the new city with the rest of the country. They built and, in some cases, extended eight highways which correspond to BR-010 to 080. Importantly for our work, the construction of this new road system that connects Brasilia with the main economic and population center accidentally achieved municipalities located near the highways.

2.3. Theoretical Framework

In this section, we follow closely the theoretical framework of Banerjee, Duflo, and Qian (2012). They argue that there are several reasons to think about how a good transportation infrastructure stimulates economic development. First, a good infrastructure could reduce trade costs due to promoting market integration. In addition, Banerjee, Duflo, and Qian (2012) highlight that good road networks facilitate factor mobility, and individuals can move easily between cities. Moreover, the connectivity between regions allows taking different opportunities for investment in human capital. Finally, Individuals can obtain intangible benefits like information or new technologies.

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the share of infrastructure spending in infrastructure reached close to 5.3% percent of GDP in 1969. In particular, since 2015 the government has invested less than 2% of GDP in infrastructure.

2.3.1. Model Assumptions

The model assumes three types of regions: M distant, N connected and one metropolis region. Thus, the economy is formed by $M + N + 1$ regions. Two types of goods are produced by each region: one consumption good and the other good exclusively for exporting. Regions also can import goods and the imported goods can be different or the same from goods that are exported.

Banerjee, Duflo, and Qian (2012) highlight that the key assumption of the model is that the relative price of the good (exportable/importable) in the market is the same p. The difference in the price of the goods is the distance to the market since the distance adds to the cost. This assumption can be modeled assuming that the transportation cost is increasing as the distance to the market increases. Therefore, the price that the exporters receive is p in the metropolis, $p(1 - d_1)$ in connected region and $p(1 - d_2)$ in the distance region $(d_2 > d_1)$.

In this economy, firms are of the same size across regions and they use two inputs (labor and capital) for production. The production for exportable goods in each region is represented by $AK^{\alpha}L^{1-\alpha}(\overline{K})^{\beta}$, where $\overline{K}$ represents the average level of K in firms in a specific region. This means that the model allows for spillovers from colocation. In addition, Banerjee et al. (2012) assume that these effects are not large enough to overwhelm the diminishing returns. Formally, this assumption can be represented as $\alpha + \beta < 1$.

Other important assumptions are related to the mobility of our two productive factors. Firstly, we assume that capital does move, but the cost of moving is large. Contrary, labor does not move and each region has an endowment: the metropolis has an endowment of L^* and the other regions have an endowment of L'. On this basis, it is reasonable to assume that the main movement happens from the various regions to the metropolis. This assumption is consistent with the Brazilian case, where the faster urbanization process from 1950 to 1970 generated a faster urban population growth (BRITO, 2006). Moreover, we also assume that when the rental rate for capital in the metropolis is r, the opportunity cost of capital in connected and distant regions can be expressed as $r(1 - \rho d_1)$ and $r(1 - \rho d_2)$, respectively.

2.3.2. Model Analysis

We will start with the assumption that firms in any region seek to maximize their profit. The maximization process is given by:

$$\max_{L,K} \left[AK^{\alpha}L^{1-\alpha}(\overline{K})^{\beta}\right][p(1-d)] - r(1-\rho d)K \tag{2.1}$$

The first-order conditions with respect to the input's yields:

$$w = p(1-d)A(1-\alpha)(\tfrac{K}{L})^{\alpha}(\overline{K})^{\beta} \tag{2.2}$$

$$r(1-\rho d) = p(1-d)A\alpha(\tfrac{L}{K})^{1-\alpha}(\overline{K})^{\beta} \tag{2.3}$$

where w represents the wage rate in a specific region. As we defined before, L is the labor endowment, K represents the equilibrium among of capital that was invested in a specific firm in that type of region and d is the distance variable. An extra constraint in the capital market is imposed, namely:

$$MK_D + NK_c + K_M = K \tag{2.4}$$

where K_C is the average of capital used in the connected region per firm, and the others K_D and K_M are defined in the same way for distant and metropolis regions. Thus, the total capital K supply in that economy cannot be higher than the sum of the capital of each region.

From the demand condition and using the definition of $\overline{K} = K$ and $L = L'$ for regions different from the metropolis, we obtain:

$$K^{1-\alpha-\beta} = \frac{p(1-d)}{r(1-\rho d)}A\alpha(L')^{1-\alpha} \tag{2.5}$$

These results show us what type of region (distant and connected) has more or less capital per firm. Specifically, the ratio $\frac{p(1-d)}{r(1-\rho d)}$ provides this information. Thus, if $\rho > 1$ the distant region has more capital per worker. The argument behind this reasoning is that, when $\rho > 1$ the capital is less mobile than goods because it is more costly to send capital to the metropolis.

From this model, we can also obtain a measure of inequality, the ratio wage/rental, as the traditional trade model does. Taking equations (2.2) and (2.3), we obtain:

$$\frac{w}{r(1-\rho d)} = \frac{(1-\alpha)(\frac{K}{L'})}{A\alpha} \tag{2.6}$$

Equation (2.6) shows us that the inequality is higher when K is lower. This conclusion can be understood through the following reasoning: assume that capital is less mobile than goods. This implies that the inequality is smaller in more distant regions since this region can retain more of its capital.

We also can represent the output per worker/capita as:

$$y = p(1-d)A(\frac{1}{L'})^{\alpha}(K)^{\alpha+\beta} \tag{2.7}$$

Substituting equation (2.5) into (2.7), we obtain:

$$y = p(1-d)A(\frac{1}{L'})^{\alpha}\left(\frac{p(1-d)}{r(1-\rho d)}A\alpha(L')^{1-\alpha}\right)^{\frac{\alpha+\beta}{1-\alpha-\beta}} \tag{2.8}$$

This equation provides interesting results, namely, when $\rho < 1$ the expression decrease in d, but increases when $\rho > 1$. This allows us to conclude that regions that are better connected lose more capital. As we mentioned before, this happens because in the connected regions the cost to move capital is lower than in distant regions.

2.3.3. Model Results

Banerjee, Duflo, and Qian (2012) draw the next conclusions from their model:

- If the capital is more mobile than goods, the output per capita will be higher and inequality lower in the better-connected regions. But, if the capital is less mobile than goods, the inequality is lower in more distant regions, the difference in per capita output between regions will tend to be small but it could be higher in the more distant regions.
- The effects of trade opening would increase the income level in the same proportion on each type of region. Consequently, it does not have differential growth effects.

2.4. Empirical Strategy

Identifying the local long-run effects of the road construction program during the military government period on economic activity twenty–five years later is a difficult task. A comparison between areas that were benefited from road construction and those that did not will probably generate biased estimates due to non-random placement. The policymaker's decision to choose road construction to pass through certain areas could be correlated with specific characteristics that might also influence their economic activity. Thus, places that receive more or better highway networks are likely systematically different from places that did not.[56] To get around such a selection problem, we use the creation of a new federal capital city Brasilia as a natural experiment. Specifically, we use OLS to estimate the following specification:

$$Y_{ast} = \alpha_a + \rho_s + \lambda_t + \mu_a \times t + \beta RoadD_{as} + Z_{mdt}\phi + \varepsilon_{ast} \quad (2.9)$$

where Y_{ast} is the log of the sum of luminosity intensity in the Microregion a, state s, and year t. The variable of interest is $RoadD_{as}$, that is the distance of centroid of microregion a to the near road, which corresponds to the kilometer of road constructed in the area a, and state s during the military government period. The vector Z including sociodemographic variables for each area. The term ε_{ast} represent the idiosyncratic error term. The model also includes microregion fixed effects (α_a) and state fixed effects (ρ_s), which absorb any unobservable time-invariant factors between microregion and states such as geographic characteristics that could confounder our estimated coefficient. Furthermore, the baseline model also includes year fixed effects (λ_t), which allows us to capture aggregates shock impacting the entire country but that can change over time. Additionally, we also control for specific-microregion linear tends $\mu_a \times t$ to take into account possible factors changing over time that might affect the outcome of interest. Finally, standard errors are clustered at the Mesoregion level to account for serial correlation (BERTRAND; DUFLO; MULLAINATHAN, 2004).

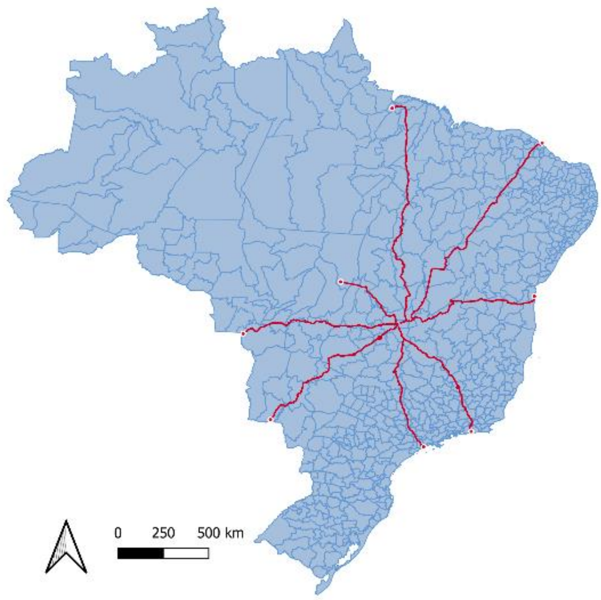
[56] On the one hand, policymakers can choose to build roads in the municipalities that display a negative growth trend with the aim of developing them. Thus, part of the effect might be associated with this negative trend, underestimating it. On the other hand, the estimated coefficients could be overestimated if the investment is done in prospering municipalities, consequently the coefficients would capture the positive trend.

2.5. Data

Road

To examine the effects of the public investment after the Brasilia creation on current economic activity, we use administrative data on road construction between 1964 and 1985. This data comes from the Institute of Applied Economic Research (IPEA, by its acronym in Portuguese). Figure 2.1 displays the road map of Brazilian radial roads connecting Brasilia.

Figure 2.1. Brazil Radial Road Connecting Brasilia



Note: Author elaboration.

Nighttime Lights

Henderson, Storeygard, and Weil (2012) have recently used satellite image data on night light density as a proxy for economic output at the disaggregated level. In a similar context to us, Storeygard (2016) uses night lights data to study urbanization among routes that connect ports in sub-Saharan Africa. We follow this line of literature and construct a panel of night-lights data to use as a proxy for economic activity.

Luminosity data come from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) provided by the National Oceanic and

Atmospheric Administration’s (NOAA) since the 1970s. Nevertheless, data are available digitally from 1992 to 2013. Each satellite observes each place on Earth every night between 8:30 to 10:00 pm local time. Data are collected and saved in a digital number (DN), which ranges from 0 to 63 with a resolution of 30 arc-second area pixels, or approximately 0,86 square kilometers at the equator.[57] The dataset covers 75°N to 65°S latitude and 180°W to 180° longitude. They are processed overlaying all daily images obtained during the calendar year, removing ephemeral lights like lightning and forest fires, those light that are shrouded by clouds or overpowered by the aurora or solar glare (near the poles), and other factors that can confound the results.

The light data have a resolution of approximately one kilometer. However, we use a raster calculator tool and aggregate us at the microregion level. Specifically, we sum up all the digital numbers across pixels for each microregion for each year and are weighted by the total area of each microregion a.[58]

Formally,

$$light_{ist} = \frac{\sum_{i=0}^{63} i*(\text{\# of pixels in microregion a,state s,and year t with DN}=i)}{Area\ Microregion\ a} \quad (2.10)$$

RAIS

Information about labor market outcomes is obtained from the *Relação Anual de Informações Sociais (RAIS)*, an administrative dataset collected by the Ministry of Labor. The RAIS records are a very rich source of data collected annually that covers all formal firms and workers, which allows us to characterize the Brazilian formal market. We use this database to delimit the information between the years 1992 to 2010, which contains a large part of our analysis period. In particular, we conduct this analysis at the micro-region level, which is economically integrated continuous municipalities that share similar geographic and productive characteristics (IBGE, 2002). Therefore, the micro-region analyses provide us with a better notion of local economies.[59] A limitation of using information from the RAIS is that this database

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[57] Note that the luminosity intensity ranking is between 0 and 63, where a value of 0 means no light and 63 the largest luminosity.

[58] Other measures of luminosity have been used in the literature like average of DN of all light pixels within a specific geographic unit or the inverse hyperbolic since (HIS) transformation (see e.g., BRUEDERLE; HODLER, 2018). We use these measures in auxiliary regression as robust tests.

[59] Several papers have carried out analysis at micro-regions in order to characterize local economies in different contexts. See e.g. Dix-Carneiro and Kovak (2017), Dix-Carneiro, Soares and Ulyssea (2018) among others.

produces information on commercial establishments and information on formal jobs. Any informally work or self-employment information would not be captured by the data.

2.6. Descriptive Statistics

Table 2.1 shows summary statistics for key variables at the microregion level used in this analysis. The data cover information about 453 microregions during the period 1992-2012. Our main independent variable, $Distance$, represent the distance in kilometers of the centroid or each microregion to the neat highway. $Night\ Light$ is the mean of night light intensity of total pixel inside each microregion.

Number Plants represent all types economic establishment of each microregion. We also have information about the number of plants of each microregion belonging to the primary and manufacturing sectors. HDI refers to the Human Development Index. We have also divided it into the three main components, schooling, longevity, and income. These variables also are available for 1991 and 2000. Electricity and population corresponds to the number of households with electricity and the total population at microregion level, respectively.

Table 2.1: Descriptive Statistics

	Observations	Mean	Minimum	Maximum
Distance (in km)	8607	296.5922	.4832323	1893.772
Night Light (mean)	8607	3.452759	.0388511	51.52816
Area (in km)	8607	1413223	1759.406	37800000
N Plants	8607	4077.664	1	282409
N Manufacture Plants	8607	449.6719	0	34168
N Primary Plants	8607	440.1124	0	4060
Population	2265	321531.3	1686	13800000
Electricity	906	69150.24	302	3642885
HDI	1359	.5184867	.1968	.824
Income HDI	1359	.5743075	.3516667	.863
Longevity HDI	1359	.7195106	.4905455	.87475
Schooling HDI	1359	.3623558	.0372	.751375

Notes: Data on 453 microregions. Distance corresponds to the distance of the microregion centroid to the nearest highway. In some specification, we use the Log(Distance) which is the logarithm of the distance and we also create dummies distance variables, D $D1$ $D2$, indicating distances less than 10, 50 and 150 kilometers, respectively. Night Light represents the mean of total luminosity pixels inside each microregion. As economic indicators, we use the number of establishments, number of primary and manufacturing establishments as a mechanism in order to explain the main relationship. Human Develop Index is also incorporated as an explanation variable in our main estimations.

2.7. Results

Table 2.2 reports the main estimation of this chapter (equation 2.9). In Column (1), we start to present the OLS coefficient without any control variable (the baseline specification), standard errors clustered at the mesoregion level are in parenthesis. The estimated coefficient is -0.252 (standard error = 0.012) and significant at conventional levels of significance. This implies that an increase of 10% in the distance to the highway is associated with a decrease of 2.52% in economic activity. Column (5) adds year fixed effect, state fixed effect, and also included (time-varying) controls including the number of houses with electricity and population at microregion level.[60] Results are very similar if we cluster at the regional level.[61] The estimated coefficient decreases to -0.166 (standard error = 0.057) but remains statistically significant. The estimated coefficient is highly similar in size to the corresponding estimate in Khanna (2016) in their OLS estimation (between -0.497 and -0.212 between 1992 and 2012). In particular, they find that an increase in distance to the National Highways in India reduces the nightlights.

The result is also in line with Bird and Straub (2020) and Damania *et al.*, (2018). Bird and Straub (2020) estimated regression of the log GDP between 1970 and 2000 on the distance to a straight line is -0.0624 in a similar context like us. Damania *et al.*, (2018) examining the impact of road upgrading in the Democratic Republic of Congo (DRC) on economic growth found that a decrease in travel cost to the local market by 1% might increase local GDP by 0.141%.[62,63] Recently, Banerjee, Duflo, and Qian (2020), analyzing the effect of transport access on regional economic activity in China, find a moderately positive effect on per capita GDP to be proximate to the transport network. In particular, Banerjee, Duflo and Qian (2020) find an elasticity of per capita GDP with respect to the distance to the transportation infrastructure is about -0.07.

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[60] Appendix Table B.1 reproduces these estimations for other measures of night-lights indicating that these results are robust.

[61] In Appendix Table B3, we use two-way clusters (region and time). In general, there are no meaningful differences between these alternative inference approaches.

[62] The cost of traveling to the cheapest market is often used as a measure of access to markets in the literature.

[63] Although our results are in line with several works in the literature, other authors have found different results in other contexts (FABER, 2014; ASHER; NOVOSAD, 2020). For instance, Faber (2014), analyzing the China's National Truck Highway System (NTHS), found that the NTHS reduces the local GDP growth among peripheral counties on the way relative to non-target peripheral counties, confirming that an improvement in the road infrastructure does not always improve economic activity. Asher and Novosad (2020) find an estimated point close to zero (0.033) when they estimate the effect of a national rural road construction program in India on the log in night-lights.

However, these authors do not find evidence on per capita GDP growth. Using also night lights as proxy for economic activity at city level, Storeygard (2016) documents that the elasticity of city economic activity with respect to the travel cost is about -0.28 at 500 km from the port. In other words, the authors find that a reduction in travel cost increases the city's economic activity. Together, the evidence shows that less distance is associated with increase in economic activity.

Finally, in Columns (6) and (7), we estimate equation 2.9 using the information on the 10 and 90th percentile of *ln(Night)* variable distribution. We can observe that the distance to the road has a greater effect in those micro-regions that have a lower intensity in the luminosity. It is to be expected that the more developed micro-regions experience little effect from the construction of a new road.

Table 2.2: Estimated Effect on Night Light Intensity

	1	2	3	4	5	6	7
Distance (in log)	-0.252***	-0.252***	-0.271***	-0.271***	-0.166***	-0.175***	-0.141*
	[0.012]	[0.012]	[0.068]	[0.068]	[0.057]	[0.060]	[0.070]
Year Fixed Effects	NO	YES	NO	YES	YES	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES	YES	YES
Population (in Log)	NO	NO	NO	NO	YES	YES	YES
Electricity (in Log)	NO	NO	NO	NO	YES	YES	YES
Observations	8607	8607	8607	8607	8607	860	861
R^2	0.077	0.102	0.566	0.591	0.655	0.766	0.517

Note: Robust standard errors in parentheses which are clustered at the mesoregion level. Table A1 in Appendix presents these results for clustering at the regional level. Column (5), our preferred specification, control for year and state fixed effect, and a specific time trend interacts with socio-economic variables. In Columns (6) and (7), in turn, we estimate equation 2.9 using the information on the 10 and 90th percentile of *ln(Night)* variable distribution.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.3 presents the results of Equation 2.9 with a different independent variable. We change the log(*Distance*), and we create three dummies variables showing the different distances to the microregion centroid to the near highway. Dummy variable *D*, *D1* and, *D2* receives a value equal to 1 if the distance to the highway is equal or minor that 50, 100 and, 150 km and 0 otherwise, respectively. Panel A shows that microregions that are at least 50 km to the highway experiment high luminosity than microregions farthest away. In Panel B, we expanding the buffer to 100 km, although the estimated coefficient decreases in all our specifications, it continues to be positive and statistically significant. This confirms that the micro-regions closest to the highways are favored with greater economic activity than those further away. In the remainder of Table 2.3, Panel C, we increase the buffer to each highway to 150 km. In the last column, the coefficient of interest is 0.38 and is significant at the 1 percent level, which implies that the microregion is closer to the road show high luminosity than the other ones.

Table 2.3: Estimated Effect on Night Light Intensity by Distance

	1	2	3	4	5
Panel A:					
D (Distance <=50KM)	0.628***	0.628***	0.628***	0.628***	0.406**
	[0.040]	[0.040]	[0.202]	[0.202]	[0.169]
Observations	8607	8607	8607	8607	8607
R^2	0.036	0.061	0.551	0.576	0.652
Panel B:					
D1 (Distance <=100KM)	0.500***	0.500***	0.531***	0.531***	0.386***
	[0.031]	[0.031]	[0.169]	[0.170]	[0.142]
Observations	8607	8607	8607	8607	8607
R^2	0.033	0.058	0.547	0.572	0.653
Panel C:					
D2 (Distance <=150KM)	0.375***	0.375***	0.483***	0.483***	0.383***
	[0.027]	[0.027]	[0.143]	[0.143]	[0.120]
Observations	8607	8607	8607	8607	8607
R^2	0.022	0.047	0.542	0.567	0.653
Year Fixed Effects	NO	YES	NO	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES
Population (in Log)	NO	NO	NO	NO	YES
Electricity (in Log)	NO	NO	NO	NO	YES

Note: Robust standard errors in parentheses which are clustered at the mesoregion level. Table B.1 in Appendix presents these results for clustering at the regional level. Column (5), our preferred specification, control for year and state fixed effect, and a specific time trend interact with socio-economic variables
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Other Related Outcomes

We now turn to an examination of others possible outcomes that could be affected by road infrastructure. We analyze how the road infrastructure changes the economic composition of each microregion. We hypothesize that an increase in road infrastructure attracts new firms or establishments to the microregion close to the highway. The potential effects of the transport infrastructure generally depend on the specific location in which they are built, therefore it is likely that they will differentially affect companies depending on the distance to the new road infrastructure. To shed light on this hypothesis, we first explore the relationship between distance to the new road construction and the number of firms or economic establishments as the outcome variable, and then we estimate this relationship separately by type of plants in order to capture any heterogeneity across industrial sectors. To do that, we compare the number of establishments in microregions closer to the highway relative to the number of plants in microregions far away.

Table 2.4 displays the estimated coefficients from Equation 2.9 using the number of plants as the outcome variable. To summarize, the empirical results show that new road transport infrastructure attracts new firms or plants. In particular, column (5), again our preferred specification, reveals that an increase of 10% in the distance to the highway is associated with a reduction in 1.2 point percent in microregions the number of plants. This result is in line with Gibbons *et al.*, (2019), who analyzed road improvement on employment and related productivity to firm outcomes in Great Britain from 1997-2008. They find that an increase in accessibility of 1% leads to a 0.3 - 0.5% increase in establishments and employment. They also find a positive impact on labor productivity measured by the gross output and average wages. Other studies find similar results in another context (CHANDRA; THOMPSON, 2000).

Table 2.4: Estimated Effect on Number of Establishment

	1	2	3	4	5
Distance (in log)	-0.409***	-0.409***	-0.343***	-0.343***	-0.128***
	[0.014]	[0.013]	[0.066]	[0.066]	[0.049]
Year Fixed Effects	NO	YES	NO	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES
Population (in Log)	NO	NO	NO	NO	YES
Electricity (in Log)	NO	NO	NO	NO	YES
Observations	8607	8607	8607	8607	8607
R^2	0.108	0.162	0.506	0.560	0.730

Note: Robust standard errors in parentheses which are clustered at the mesoregion level. Column (5), our preferred specification, we control for a year and state fixed effect, and a specific time trend interacts with socio-economic variables.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.5 disaggregates the number of establishments by type of industrial sector using Equation 2.9. In Panel A the estimation is carried out with the number of plants in the manufacturing sector as the outcome variable while in Panel B the outcome variable is the number of plants in the primary sector. The first point to note is that the estimated coefficients are negative and statistically significant at the conventional level. Looking at column (5) in Panel A, we find that an increase in 10% in the distance to the highway ways is associated with a decrease in the number the plants by 1.6 points percent in the manufacturing sector while for the primary sector the decrease in around 0.2 points percent (Column 5 Panel B), although not staticsally significant. This result indicates the importance of taking into account the heterogeneous impact across the economic sector in order to better direct policies.

Table 2.5: Estimated Effect on Number of Establishment by Type of Establishment

	1	2	3	4	5
Panel A: Manufacturing Sector					
Distance (In Log)	-0.366***	-0.367***	-0.387***	-0.388***	-0.166***
	[0.015]	[0.015]	[0.073]	[0.073]	[0.056]
Observations	8501	8501	8501	8501	8501
R^2	0.075	0.098	0.481	0.506	0.669
Panel B: Primary Sector					
Distance (In log)	-0.403***	-0.404***	-0.115*	-0.116*	-0.025
	[0.013]	[0.013]	[0.061]	[0.061]	[0.064]
Observations	8460	8460	8460	8460	8460
R^2	0.075	0.118	0.640	0.688	0.724
Year Fixed Effects	NO	YES	NO	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES
Population (in Log)	NO	NO	NO	NO	YES
Electricity (in Log)	NO	NO	NO	NO	YES

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

2.8. Conclusion

If road transport infrastructure is key to promoting economic growth, studying the potential effects and their persistence in developing countries is crucial to understand how the economic growth process is carried out. In this chapter, we use a natural experiment, the creation of the new Brazilian capital Brasilia, and the consequent construction of new roads that connected the new capital with the other main economic and population nodes of the country to estimate the long-lasting effects on economic activity. In sum, our results reveal that microregions closer to the highway present better economic performance measures as the night light intensity than microregions far away.

Our exploration of other economic outcomes suggests that the increase in the night light intensity as a consequence of the new road infrastructure can be explained by the increase of the number of plants in microregions located closer to the highways. These findings have potential policy implications. New infrastructure projects should take into account the spatial relocation of economic activity in areas surrounding these types of projects. Although extensive literature has already documented the positive effects of new infrastructure projects on economic activity, knowing the potential economic effects at a disaggregated geographic level could improve efficiency in the distribution of public resources. Once there is information on the economic profits at the local level, one could have information on the gains/losses in the spatial relocation of the economic activity. It is also important to highlight some limitations of our study. We do not have information about the light night intensity before the Brazilian creation, therefore, we do not carry out a different identification strategy to support our main results. Future research could analyze also the effects of infrastructure projects on environmental variables at a disaggregated level. That is, analyze those areas that suffer more or less environmental damage with the construction of new infrastructure projects.

Appendix B

In this section, we implement an alternative outcome variable for our main specification in Equation 2.9. Especially, we use the mean of the night light intensity of each microregion and the mean of the night light weighted by the population of each microregion in 1992. The results are present in Table B1 in Panel A and Panel B, respectively. We also examine an alternative specification of equation 2.9 to show the robustness of our key findings. In particular, we use dummies variables indicating the distance to the highway as the independent variable and the mean of the night light intensity as the outcome variable, Table B2 displays the results of this exercise.

Table B.1: Estimated Effect on Night Light Intensity

	1	2	3	4	5
Panel A:					
Distance (ln log)	-0.248***	-0.248***	-0.278***	-0.278***	-0.170***
	[0.012]	[0.011]	[0.072]	[0.072]	[0.060]
Observations	8607	8607	8607	8607	8607
R^2	0.078	0.106	0.517	0.546	0.618
Panel B:					
Distance (ln log)	-0.047***	-0.047***	-0.038	-0.038	-0.087*
	[0.010]	[0.010]	[0.043]	[0.043]	[0.049]
Observations	8607	8607	8607	8607	8607
R^2	0.003	0.038	0.421	0.456	0.475
Year Fixed Effects	NO	YES	NO	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES
Population (in Log)	NO	NO	NO	NO	YES
Electricity (in Log)	NO	NO	NO	NO	YES

Note: Robust standard errors in parentheses which are clustered at the region level. Column (5), our preferred specification, control for year and state fixed effect, and a specific time trend interacts with socio-economic variables.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table B.2: Estimated Effect on Night Light Intensity by Distance

	1	2	3	4	5
Panel A:					
D (Distance <=50KM)	0.643***	0.643***	0.649***	0.649***	0.419**
	[0.041]	[0.040]	[0.224]	[0.224]	[0.189]
Observations	8607	8607	8607	8607	8607
R^2	0.039	0.067	0.501	0.530	0.615
Panel B:					
D (Distance <=100KM)	0.528***	0.528***	0.576***	0.576***	0.427***
	[0.031]	[0.030]	[0.185]	[0.185]	[0.157]
Observations	8607	8607	8607	8607	8607
R^2	0.038	0.067	0.499	0.528	0.618
Panel C:					
D (Distance <=150KM)	0.382***	0.382***	0.495***	0.495***	0.392***
	[0.027]	[0.026]	[0.156]	[0.156]	[0.131]
Observations	8607	8607	8607	8607	8607
R^2	0.024	0.052	0.491	0.519	0.615
Year Fixed Effects	NO	YES	NO	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES
Population (in Log)	NO	NO	NO	NO	YES
Electricity (in Log)	NO	NO	NO	NO	YES

Note: Robust standard errors in parentheses which are clustered at the region level. Column (5), our preferred specification, control for year and state fixed effect, and a specific time trend interact with socio-economic variables
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Robust Inference

In our main estimation Table 2.2, we cluster standard error at the mesoregion level because the night light intensity can be correlated spatially. In Table B3, we estimate our main results using cluster standard error at region level and time. A possible concern with our main estimation is that the standard error can be correlated across time.

Table B.3: Estimated Effect on Night Light Intensity (Different Clusters Specification)

	1	2	3	4	5	6	7
Distance (in log)	-0.252***	-0.252***	-0.271***	-0.271***	-0.166***	-0.175***	-0.141***
	[0.012]	[0.012]	[0.016]	[0.016]	[0.013]	[0.021]	[0.020]
Year Fixed Effects	NO	YES	NO	YES	YES	YES	YES
UF Fixed Effects	NO	NO	YES	YES	YES	YES	YES
Time trends interacted with:	NO	NO	NO	NO	YES	YES	YES
Population (in Log)	NO	NO	NO	NO	YES	YES	YES
Electricity (in Log)	NO	NO	NO	NO	YES	YES	YES
Observations	8607	8607	8607	8607	8607	860	861
R^2	0.077	0.102	0.566	0.591	0.655	0.766	0.517

Note: Robust standard errors in parentheses which are clustered at the region level and time. Column (5), our preferred specification, control for year and state fixed effect, and a specific time trend interacts with socio-economic variables. In Columns (5) and (6), in turn, we estimate Equation 2.9 using the information on 10 and 90th percentile of *ln(Night)* variable distribution..
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

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Chapter 3
Coffee Price Shock and Local Economic Activity: Evidence from Colombia

Abstract

This study provides evidence of how commodities price shocks affect local economic activity in Colombia. The identification strategy exploits the interaction between international coffee prices and municipal intensity in coffee production. Using satellite images of light density at night as a proxy of local economic activity, we document a positive and strong effect of coffee price shock on the local economic activity. We also examine some other related variables that can be impacted by the boom in coffee prices.. Results reveal that more illuminated areas report better schooling outcomes and a reduction in mortality. Our findings help to understand the economic dynamic in an accurate way at the sub-national level in Colombia, where data about GDP at the municipality level are not available.

JEL codes: Q17; E01; O11

Keywords: Nighttime Light. GDP. developing country.

3.1. Introduction

Many studies have investigated the effects of commodity price shocks on the economic activity at the national level in both high- and low-income countries (MICHAELS, 2011; ACEMOGLU; FINKELSTEIN; NOTOWIDIGDO, 2013; CASELLI; MICHAELS, 2013, among others). However, despite the Gross Domestic Product (GDP) standing out as a traditional indicator used to analyze these effects, scholars usually have to deal with some inconsistencies and biases that could arise in their estimated results. This is because GDP itself is often inadequately measured, mainly in developing countries (HENDERSON; STOREYGARD; WEIL, 2012). By contrast, few papers have analyzed whether these effects vary at a more disaggregated level. The difficulty in this type of analysis is related to the unavailability of data at the subnational level; official authorities in developing countries often do not have the infrastructure and resources to generate accurate statistical data on GDP.

There are several reasons to think that the commodity price shocks may affect economic activity differently across small geographic areas. On the one hand, areas that are intensive in the production of a specific commodity may be more affected by exogenous supply or demand shocks than areas that are not intensive or have no production. For example, commodity price booms are expected to increase consumption and investment in intensive areas, once producers receive higher income with the same quantity sold. Thus, they will be able to consume and invest more. Consequently, economic activity in these areas could be higher than in low intensive areas. On the other hand, areas that are not intensive may not suffer any effect of exogenous shocks on commodities or may be affected by spillover effects from those areas that are intensive in production. Thus, understanding what are the effects of macroeconomic shocks at a disaggregated level and how these shocks propagate through time and space are issues not well understood.

This paper studies these questions by examining the effects of shock in the world coffee prices on the local economic activity in Colombia measured as intensity of night-lights.[64] We do this by exploiting the variation in international coffee prices and the geographic distribution of coffee production, which enables us to assess how the changes in the economic environment affected the Colombian municipalities' economic activity between 1992- 2005.[65] We also analyzed whether this shock propagates over time and across geographic areas. In particular, we focus on the period between the years 1994-1997 when the world coffee prices increased sharply as a consequence of a severe frost episode in Brazil that destroyed a large part of the crops in that country. During this period the international coffee prices increased from $1.53 per kilogram in 1993 to $4.17 in 1998.

The use of luminosity data as a proxy of economic activity has been documented and tested in the pioneering work by Henderson, Storeygard, and Weil (2012). We could expect that most human activities in the evening, represented as more consumption and more production, required more artificial lights. This could be

[64] Other measures of economic activity have been used as proxies of GDP such as electricity consumption. However, electricity consumption data often are not available for many countries at sub-national level. In the case of Colombia, electricity consumption information is not available over time and at the municipality level

[65] Municipalities are the lowest administrative level unit in Colombia, which are within the 32 departments. Departments are analogous to states in the United States while municipalities are equivalent to counties.

understood because the majority of goods used at night need lights. Therefore, we could assume that regions with more light intensity are regions with more economic activity (ELVIDGE *et al.*, 1997; DOLL; MULLER; MORLEY, 2006; CHEN; NORDHAUS, 2011; PINKOVSKIY; SALA-I-MARTIN, 2016). Consequently, we would expect that its income to be higher (HENDERSON; STOREYGARD; WEIL, 2012; LESSMANN; SEIDEL, 2017). In this order of ideas, it seems reasonable to assume that nightlights can be used as a proxy of GDP for regions where data are poorly measured or data are not available. To shed a light on this hypothesis, we provide consistent evidence on the relationship in our empirical application at the low level of geographical aggregation in Colombia.[66]

The use of luminosity data is attractive for several reasons. First, this data could help to deal with potential problems of no availability or little reliability that plague official data in developing countries (HENDERSON; STOREYGARD; WEIL, 2012; CHEN; NORDHAUS, 2011; SUTTON; COSTANZA, 2002). Colombia is an example of this lack of information and data on GDP at the municipality level does not exist.[67] Second, luminosity data are available over time and for all places on Earth with uniform measure and over the very fine level of resolution. Finally, even though potential problems concerning measurement errors can appear, related to how the satellite captures the lights, or climatic conditions, or human culture in the use of lights, this kind of measurement error is not correlated with traditional GDP data errors (PINKOVSKIY; SALA-I-MARTIN, 2016).

Our identification strategy compares the night-light intensity of producing and non producing municipalities before and after coffee price shocks in a difference-in-difference approach. The identification strategy relies on the assumption that coffee price shocks disproportionately affect areas with high suitability to produce coffee.

Two major results emerge from our analysis. First, we find differential and statistically significant increases in the night-light intensity in municipalities that produce more coffee when the price rises exogenously. In particular, the estimated coefficient from our preferred specification reports an elasticity in coffee price shocks

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[66] For a first view of the validity of this hypothesis, Figures C.1 and C.2 in the appendix show a plot of log GDP and log lights for the country as a whole and at the department level. We can observe a strong and positive relationship.

[67] To the best of our knowledge, the most disaggregated data on GDP that is available in Colombia is at the department level.

of 0.20, which represents an increase of 0.26 percent relative to the baseline mean. We also show that our results are robust concerning different specifications. In particular, we confirm that the results are robust concerning control for municipality and year fixed effects, municipality-specific linear time trends, different cluster specifications as well as control by a set of socio-economic characteristics of municipalities. Importantly, we obtain similar results when we use different night lights density measures.

Having established that the coffee price shock has a robust effect on nighttime lights, we then present suggestive evidence for some related economic outcomes that the coffee price boom could have affected. We focus on two factors that have been traditionally linked by the literature to local economic conditions: schooling and mortality rates. First, we use the 2005 Colombian Demographic Census to construct the average of years of education by municipalities for the population with 25 or more years old and then we estimate the link between light nigh intensity and years of education. The estimates suggest that areas with greater luminosity reflect higher years of education. Consistent with our results, there is some evidence showing that geographic units (counties, states, countries) with better economic condition reflected in more school resources have a positive effect on years of education (see e.g., CASE; DEATON, 1999; DUFLO, 2001; PAXSON; SCHADY, 2002; CARD; KRUEGER, 1996).

Second, using data about a vital statistic from the Colombian National Administrative Department of Statistics (DANE), we construct the mortality rate of each municipality. Then, we estimate our preferred specification using mortality rate as the dependent variable. A reduction of the mortality variable could be interpreted as an increase in survival chances, which could reflect better economic conditions in that specific area. We show that an increase of 1 percent in our coffee shock variable is associated with a decrease in the mortality rate.

This paper is related to a large literature that uses satellite images as a proxy of economic activity (see e.g., PINKOVSKIY; SALA-I-MARTIN, 2016; ALESINA; MICHALOPOULOS; PAPAIOANNOU, 2016; MICHALOPOULOS; PAPAIOANNOU, 2013; HENDERSON; STOREYGARD; WEIL, 2012, among others). For example, Michalopoulos and Papaioannou (2013) use luminosity data to investigate the role of deeply-rooted pre colonial ethnic institutions over regional development in Africa. Alesina et al. (2016), in its turn, construct measures from luminosity data to investigate the consequences and origins of ethnic inequality. Specifically, they find evidence of those geographic endowments between ethnic countries that could explain inequality. Pinkovskiy and Sala-I-Martin (2016) use nighttime lights as tools to show how much weight is necessary to give to national accounts GDP per capita and household surveys to obtain a better predictor of income. They find that the best predictor of the log of true income must receive nearly 100% of the weight on GDP per capita.

Our work is also related to the voluminous literature that assesses the effects of macroeconomic shocks on several local economic variables (see e.g., ACEMOGLU; FINKELSTEIN; NOTOWIDIGDO, 2013; MONTEIRO; FERRAZ, 2010; CARRERI; DUBE, 2017, among others). Acemoglu, Finkelstein, and Notowidigdo (2013), for example, using oil price shocks as an instrument for income, assess the changes in health spending in the southern United States. Monteiro and Ferraz (2010), in its turn, analyzing how the increase in Brazil's oil production affects local democracy find that royalty payments produce a large incumbency in the short term.

Most closely related to our study are the contributions of Dube and Vargas (2013), Miller and Urdinola (2010), Carrillo (2020), Albertus (2019), and Santos (2018). Dube and Vargas (2013), for example, show how the commodities price shocks affect armed conflict in Colombia. More specifically, the authors document that changes in the price of agricultural goods are negatively related to violence, while changes in the price of natural resources are positive. Meanwhile, Miller and Urdinola (2010), exploiting world coffee price fluctuations in order to examine the cyclical nature of infant and child mortality in Colombia, find a procyclical relationship in child death. Carrillo (2020), in turn, also exploiting the variation in world coffee prices and variation in coffee cultivation patterns in Colombia, provide suggestive evidence on the long-run impacts of commodity price shocks. The results reveal that cohorts who faced more exposure to the coffee boom in childhood completed fewer years of schooling and they also have lower adult income earnings. Finally, Santos (2018) analyzing the gold boom found a decrease in local unemployment by 3.5% in the short term in Colombia. To the best of our knowledge, the present study is the first to exploit a quasi-experimental design to empirically investigate the relationship between coffee price shocks and a more accurate measure of local economic outcome (night-lights density) in Colombia. As a product of this analysis, our findings also contribute to a new estimation of economic outcome for Colombia at the municipality level.

The remainder of this paper is structured as follows. Section 2 briefly reviews the Colombian coffee market. Section 3 describes the data and how our variables were constructed. Section 4 presents the empirical strategy. Section 5 provides the main results and robustness tests. Finally, section 6 concludes.

3.2. Background

3.2.1. Coffee Production in Colombia

As noted above, Colombia is well known for being one of the largest coffee producers in the world. During the largest part of the 20th century, the Colombian economy was associated with coffee production, which has played an important role in the development and economic growth of the country (CÁRDENAS; YANOVICH, 1997). In particular, coffee has been the second largest export commodity during the decade of the 90s. During our study period, coffee was the most important agricultural sector. Given its nature time- and labor-intensive process, the sector represented around 1.7 and 23.9 percent of the total GDP and the agricultural GDP between 1995 and 1999, respectively (GIOVANNUCCI *et al.*, 2002).[68] Bearing this in mind, the Colombian coffee harvest process employs a larger number of workers than in other agricultural sectors. Specifically, at the beginning of the 90s, the coffee sector represented near 34 percent of the agricultural employment, which could be translated into 750 thousand full-time jobs (JUNGUITO; PIZANO, 1991). Furthermore, in 1997, 18 percent of rural households' income depended directly on coffee production (GIOVANNUCCI *et al.*, 2002).

Most coffee production in Colombia is distributed in the mountainous region, at the departments of Antioquia, Caldas, Quindio, and Risaralda. The coffee production is concentrated in these areas due to its agro-climatic condition, which makes them more suitable for coffee growing. The entire coffee harvesting area in our sample is made up of 549 municipalities, which represent 56% of the total Colombian municipalities'.

Over the years it has been identified that ideal agro-climatic conditions for the coffee-growing are associated with temperatures varying between 18 and 24 degrees

[68] Coffee production process is intensive in time and labor due to the farming method implemented in Colombia. Mainly, the production process is carry out by hand given in part because the area where it is mostly cultivated is a mountainous area, so it is difficult to mechanize the production process, at least in a large part.

Celsius, annual rains ranging from 1500 to 2000 approximately, and relativity humidity oscillating between 70 and 90 percent (CLIFFORD, 2012). Areas satisfying this climatic condition are potentially coffee producers. In some regions, according to its agro-climatic conditions, coffee can be produced all year in two harvests. The main harvest is carried out between October and December, and the second between April and May. We will take advantage of these environmental conditions in our empirical strategy. In particular, we carry out some alternative IV regression where rainfall and temperature are instruments for coffee intensity to overcome some endogeneity problems.

It is worth highlighting the relevance of this sector in the national economy and analyzing what are the potential dynamics of the sector due to external shocks is of vital relevance for policymakers. In particular, knowing the potential effects of external shocks could provide useful information for the elaboration of public policies or contingency plans to overcome sudden booms and/or busts in the market.

3.2.2. Night Lights Data and Economic Activity

From the last decade, economists are increasingly turning to data from satellite images as an alternative or supplementary measure of economic activity. Economic literature has recently focused the attention on night light data capability to use as a proxy for economic activity, especially in countries and territories where official statistics of the economic indicator are not available (CHEN; NORDHAUS, 2011; DOLL; MULLER; MORLEY, 2006; EBENER *et al.*, 2005; ELVIDGE *et al.*, 1997; SUTTON; COSTANZA, 2002; HENDERSON; STOREYGARD; WEIL, 2012; GHOSH *et al.*, 2010; PINKOVSKIY; SALA-I-MARTIN, 2016).[69,70]

These studies have made substantial progress mainly in two fields. They have been concerned with obtaining consistent estimates of the level of economic activity such as Purchasing Power Parity (PPP) and real and nominal GDP as well as disaggregated estimates of this measure into smaller administrative/non-

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[69] Early papers have used luminosity in order to analyze whether night lights reflect socioeconomic indicators at different levels of aggregation in low-income countries. Elvidge *et al.*, (1997) studying the statistical correlation between night light and GDP at the country level found a strong correlation of 0.97 for 21 countries. In a similar way, Sutton and Costanza (2002) carry out estimation and show a correlation between night light and GDP per square kilometer at national level. Ebener *et al.*, (2005), in turn, take advantage of night light data to forecast income per capita a sub-national level.

[70] For extensive reviews of research using satellite data, especially luminosity, see Donaldson and Storeygard (2016) and Michalopoulos and Papaioannou (2018).

administrative areas. Chen and Nordhaus (2011) and Henderson, Storeygard, and Weil (2012) are seminal papers that introduce the night lights as an alternative measure of economic output. Chen and Nordhaus (2011), for example, show that the night light adds informational value to a standard measure of GDP for countries, regions, and areas with low quality of statistics collection systems or missing data. In the same line, Henderson, Storeygard, and Weil (2012) introduce the night light data into economics, using an error-measurement approach that combines night light intensity measure with standard statistics to generate an accurate estimation of economic growth rates for a panel of 188 countries. The authors find that a mix of traditional measured growth and growth predicted from night lights with equal weights is considered an optimal estimation of growth. In particular, they find an elasticity of the long-term growth in lights related to the long-term GDP growth is 0.32 and R^2 of 0.28, suggesting that night lights data improve the quality and availability of economic indicators like GDP especially in countries where statistical agencies are not stronger. Nevertheless, they found that luminosity adds moderate value to national statistics in countries with high-quality statistics systems.[71]

Despite the small contribution of night lights in countries with well-developed and strong information systems, Henderson, Storeygard, and Weil (2012) also offer new insights about the importance of night lights due to their spatial granularity. Taking this into consideration, many scholars have gone beyond and exploited the availability and granularity of night lights to make analyses at the local level. Thus, night light intensity data are becoming a widely used measure of economic outcomes (economic activity or economic development) at the subnational administrative level.[72]

In this line of research, Nordhaus and Chen (2015) estimate the optimal weights on standard GDP and night light intensity data to calculate the true output at country and grill cells level between 1992 and 2010. They find that for countries with A and B grades, there is no reason to use night light data as a supplement of national statistical

[71] These results are similar to those found by Chen and Nordhaus (2011). The authors argue that standard economic data in high-income countries have relatively small measurement errors and they are available with great frequency to compare with the high measurement error of night light density data, which makes the estimation of economic activity more accurate.

[72] Doll, Mulle, and Morley (2006) estimate the relationship between nighttime data and the available Gross Regional Product (GRP) of 11 European Union countries and along with states in the United States. The authors find that nighttime lights are strongly correlated with the GRP at different spatial scales. More specifically, their estimates suggest that the elasticity of the GRP on the sum of night light intensity is within the range of 0.049 and 0.210 in these regions.

data when traditional data are available at country or grid cell level while countries with grade C light data could be useful.[73]

Given some limitations with the use of luminosity data as a proxy for the economic outcome, several types of research provide robust evidence that luminosity data can be used as a good proxy for economic output. In an interesting framework, Hodler and Raschky (2014) exploit the information of the birthplaces of the political leaders of 126 countries to find evidence of regional favoritism. They notice that sub-national regions where a current political leader was born are benefited by national investments and these investments are reflected with greater intensity in the night lights compared to other regions, providing evidence of regional favoritism. Moreover, Hodler and Raschky (2014) estimated results suggesting that being the leader region increases the night light intensity by approximately 4 point percent while the GDP increases by 1 point percent. In the same spirit, De Luca *et al.*, (2018) construct a data set of several thousand subnational ethnographic regions from around 140 multi-ethnic countries and also find evidence of regional favoritism. Their findings show an increase of 7 - 10 point percent on average of nigh light intensity and 2-3 point percent higher GDP if the current political leader belongs to this region.

Another body of literature focuses on different socio-economic indicators to assess whether night lights can reflect the well-being of populations in small geographical areas. For example, Michalopoulos and Papaioannou (2013), using data from the Demographic and Health Surveys (DHS) of Zimbabwe, Tanzania, Nigeria, and the Democratic Republic of Congo, shows a significant regional correlation between nighttime lights intensity and measures of well-being. Similarly, Bruederle and Hodler (2018) construct different socio-economic indicators from geo-referenced DHS from 29 African countries to establish the relationship of these indicators with night light density information. They find a positive and strong correlation with household wealth, education, and health suggesting that night lights can be a good proxy for economic development at the local level.

[73] The authors of the Penn World Tables, Robert Summers and Alan Heston, have assigned a subjective classification to the countries that can be from A to D according to the quality of their national accounts data. Thus, countries with high degrees of quality, that is, lower margins of error in their estimates of Penn World Tables GDP receive a better classification (A), while countries with bad data quality receive (D). Chen and Nordhaus (2011) add grade E for those countries that do not have statistical systems or countries that do not appear in PWT and other standard sources of information.

Elvidge *et al.*, (2012), in their turn, in a cross-country analysis find a positive correlation between nighttime lights when they analyzed the Human Development Index (HDI) and electrification rates. They also find that the relationship is negative when they analyze poverty rates but they do not find a statistical relationship with the traditional Gini index. Consistent with this evidence, Jean *et al.*, (2016) use machine learning techniques and satellite images to make small-scale poverty predictions for 5 African countries. Specifically, they take advantage of daytime satellite photos to capture details of the land space and night lights satellite as a proxy for economic activity.

Night lights have also been used as a proxy to estimate regional inequality. Alesina, Michalopoulos, and Papaioannou (2016) present evidence of inequality in well-being across a large number of countries. They combining linguistic maps on the spatial distribution of ethnic groups within countries with night light satellites to construct the Gini index. Recently, in the same field, Lessmann and Seidel (2017) estimate regional inequality using night light density information to predict regional incomes within countries where information is missing.

Due to these large number of promising results, light data might serve as a useful proxy for economic output because it is 'objectively' measured, is highly correlated with output, and is universally available for the world except for the high latitudes.

3.2.3. Linking Coffee Price Shock and Night Lights Intensity

In the previous subsection, we have shown a wide range of contexts where night lights have been used as a proxy for economic results. However, few studies have analyzed how exogenous price shocks affect economic activity as measured by night lights.[74] Gradstein and Klemp (2020); Smith and Wills (2018) are exceptions. For the Colombian case, Rozo (2016) analyze the effects of natural resource booms on local development measures by night lights intensity.[75]

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[74] There is an extensive literature that has analyzed the effects of shocks on international prices in different contexts. This literature has focused on the effects of changes in health expenditures (ACEMOGLU; FINKELSTEIN; NOTOWIDIGDO, 2013), crime (ANDREWS; DEZA, 2018) and, schooling (BRUECKNER; GRADSTEIN, 2016).

[75] Rozo (2016) exploits the international price shocks in municipalities that have preexisting reserves of gold, coal, and oil and estimate the effects on the local economic development measure as the night light intensity. The author estimations suggest that an increase in international prices of oil and gold

We can understand intuitively how the exogenous increase of international coffee prices is related to the night lights intensity as follow. An increase (decrease) in international coffee prices could increase the income received by the coffee producers, and once most Colombian coffee producers are small, household income could increase (decrease). This increase (decrease) in the household income may encourage (discourage) the household member to consume more (less) goods and services. Consequently, increases (decrease) in goods and services can increase (decrease) the economic activity.

Additionally, increases in economic activity can be reflected, on the one hand, in increases in the production of goods and services. As the majority of companies that produce consumer goods use machinery that demand electricity this would increase the intensity of the lights if part of their production process takes place at night. Alternatively, households with higher income levels may buy more consumer goods such as appliances, many of which need the energy to function. Given the importance of this sector, the favorable environmental conditions that are necessary for coffee cultivation, and the high quality and availability of data, the study of the coffee market becomes very attractive.

3.3. Theoretical Framework

We start our analyses by developing a simple theoretical model to provide us a framework to interpret the results. Following the microeconomic theory of consumer behavior, we assume that the decision for night light demand is based upon income, the price of night light, the prices of other goods different from night lights, and other factors that can affect night light consumption. Thus, the consumption function for night lights can be represented as follow:

$$LD_{i,t} = f\left(Y_{t,i}\ ,\ P_{L_{t,i}}\ ,\ P_{NL_{t,i}}\ ,\ A_{t,i}\right) \tag{3.1}$$

where $LD_{i,t}$ denote the night light intensity in time t in geographic area i, which is an function of income (Y), night light price (P_L), other goods price (P_{NL}) and other factors that potentially can influence the night light (A).

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affect positively the local development measure as the night light in producing municipalities relative to non-producing. Furthermore, Rozo (2016) finds negative effects in the coal sector.

We can assume that A can represent the technology, which can be a function of prices and income. So, equation 1 can be rewritten as:

$$LD_{i,t} = f\left(Y_{t,i}\,, P_{L_{t,i}}\,, P_{NL_{t,i}}\,,\ A_{t,i}\left(P_{L_{t,i}}, Y_{t,i}\right)\right) \tag{3.2}$$

For simplicity, we assume that, for a given level of economic development, energy price and technology are common across municipalities. We also assume that the price of other goods is equal to one. Thus, we can express the night light function such as:

$$LD_{i,t} = \hat{f}\left(Y_{t,i}\,, P_{L_{t,i}}\right) \tag{3.3}$$

Now, suppose that there is a shock in the income of the municipalities caused by an increase in the coffee price (P_c):

$$\frac{\partial LD_{i,t}}{\partial P_c} = \frac{\partial LD_{i,t}}{\partial Y_{t,i}}\frac{\partial Y_{t,i}}{\partial P_c} \tag{3.4}$$

Suppose now that the night light demand function can be represented by:

$$LD_{i,t} = P_{t,i}^{\beta_1} Y_{t,i}^{\beta_2+\beta_3 lnY_t} \tag{3.5}$$

We assume this functional form because it allows us a non-constant income elasticity of the demand for luminosity.[76] Upon taking logarithms:

$$lnLD_{i,t} = lnA + \beta_1 P_{t,i} + \beta_2 lnY_{t,i} + \beta_3 ln\left(Y_{t,i}\right)^2 \tag{3.6}$$

The term A can be replaced by $(\lambda_t + \theta_i)$ which represents time fixed effect and municipalities fixed effect, respectively. Thus, equation (6) can be written as follow:

$$lnLD_{i,t} = (\lambda_t + \theta_i) + \beta_1 P_{t,i} + \beta_2 lnY_{t,i} + \beta_3 ln\left(Y_{t,i}\right)^2 \tag{3.7}$$

3.4. Empirical strategy

3.4.1. Fixed Effect Estimation

The empirical strategy follows a difference-in-difference estimator and seeks to examine whether changes in international coffee prices have a different impact in areas that are more suitable to produce more coffee on local economic activity measured as the nightlight intensity. Thus, to obtain the causal effects, we could compare the intensity of the light in producing and non-producing municipalities before and after the

[76] Other types of functional form can be adapted to allow greater flexibility. However, we use this for simplicity.

shock of prices. The key independent variable is the interaction between the log of the annual average of international coffee prices and the intensity of coffee production in each municipality in 1997. Thus, we can interpret this variable as our measure of exposition to the price variation or macroeconomic shocks. In particular, we estimate the following model:

$$l_{mdt} = \alpha_m + \rho_d + \lambda_t + \mu_m \times t + \beta(Coffee_{md} \times PCoffee_{avt}) + \phi Z_{mdt} + \xi_{mdt} \qquad (3.8)$$

where l_{mdt} is the log of the sum of luminosity intensity in the municipality m, department d, and year t; $Coffee_{md}$ represents a measure of land destined to coffee production in 1997 for each municipality; $PCoffee_{avt}$ represents the annual average of the natural log of the international coffee prices. The vector Z including time-varying controls, like the natural log of population, that are included in some of our specifications. The model also includes municipality fixed effects (α_m) and department fixed effects (ρ_d), which absorb any unobservable time-invariant factors between municipalities and departments such as geographic characteristics that could confounder the coefficient. We also include year fixed effects (λ_t), which captures aggregate shocks impacting the entire country but that can change over time. The term ξ_{mdt}, in its turn, is the idiosyncratic error term. Finally, we also control for specific-municipality linear tends $\mu_m \times t$ to take into account possible factors changing over time that might affect the outcome of interest.

The parameter of interest is β, which represents the effect of price shock on the night light intensity. Despite the results of the fixed effect model being attractive, some potential endogenous problems can appear with this framework, even after we controlled for a set of relevant geographic and economic characteristics. Therefore, the OLS estimate of β would be the effect of price shocks and a bias. In the next subsection, we explain the potential problems that may arise, their implications, and how we will overcome them.

3.4.2. Instrumental Variable Estimation

Two potential endogeneity problems could threaten the validity of our empirical strategy. On one hand, we could face coffee price endogeneity due to Colombia's rank as the second exporter during a large part of our time of study and this could influence the international coffee prices (DUBE; VARGAS, 2013). Once producers are aware of the decline in the international supply of coffee, keeping demand constant, they may have incentives to increase their coffee prices which would further increase international prices. This potential increase in international coffee prices would further increase the producers’ income and consequently, the brightness would increase. This context would lead us to overestimate the impact of coffee prices as a result of the decline in international supply. Following Dube and Vargas (2013), we address this concern using data on the export volume of Brazil, Indonesia, and Vietnam, the other three major coffee producers, as an instrumental variable for the internal coffee price. This approach permits us to capture changes in the internal coffee price that are resulted due to changes in the export supplies of these countries.

On the other hand, coffee production could be endogenously determined because our coffee production intensity variable is a measurement that was taken during our analysis period (1997). One might expect these producers to have incentives to increase their production once prices have increased and their opportunity cost of producing is higher. As a consequence, economic activity in a specific area increases as the intensity of luminosity increases. We believe that this threat is unlikely given that coffee new plants require between 3 and 4 years before the tree gives the first fruits. Thus, if producers plant new plants in 1994, for example, the first fruits can only be harvested until 1999, and as can be seen in figure 3.1, in this year prices began to decrease.[77] Nevertheless, to deal with this potential issue, we follow the strategy proposed by Dube and Vargas (2013), and instrumentalize coffee intensity with rainfall and temperature for each municipality.[78] Rainfall and temperature could be excellent candidates for instruments because geographic conditions of each municipality determine which are more suitable to produce coffee and which are not.[79] Formally, we can carry out the estimation in two-stages least squares. The second stage can be specified as:

$$l_{mdt} = \alpha_m + \rho_d + \lambda_t + \mu_m \times t + \beta\left(\widehat{Coffee_{md} \times PCoffee_{avt}}\right) + \phi Z_{mdt} + \xi_{mdt} \qquad (3.9)$$

The first stage for coffee, in its turn, can be represented as:

$$Coffee_{md} \times PCoffee_{avt} = \alpha_m + \rho_d + \lambda_t + \mu_m \times t + \beta(R_{md} \times T_{mt} \times FE_t) + \phi Z_{mdt} + \xi_{mdt} \qquad (3.10)$$

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[77] International coffee prices began to recover from the year 2000 mainly due to the recovery of crops in Brazil and the extension of the coffee market in Vietnam.
[78] See Miller and Urdinola (2010) for a similar approach.
[79] See section 2 for details about these conditions.

where R_{md} is the average annual rainfall of municipality m of department d; T_{mt} n is the average annual temperature of municipality m of department d; FE_t is the log coffee export volume of Vietnam, Brazil, and Indonesia; all exogenous variables considered in the second stage are included in this stage also. More specifically, the model includes a vector Z that is a set time-varying control, municipality fixed effects (α_m), year fixed effects (λ_t), and we also control for specific-municipality linear $\mu_m \times t$. Our main estimation uses 2SLS and all our models use robust standard errors for clustering at the department level to control for potential serial correlation (BERTRAND; DUFLO; MULLAINATHAN, 2004).

The parameter of interest is β in Equation 3.9, which shows us the differential impact of coffee price shock on the economic activity in municipalities that are more suitable to produce coffee. The key identifying assumption of our approach is that in the absence of coffee price shocks, municipalities with different coffee production have experienced the same proportional changes in light-night intensity. We also exploit the fact that this commodity is not uniformly distributed all over the country. In fact, its distribution depends on demographic characteristics (temperature and rainfall) as we have mentioned before. Therefore, we can assume that any effects of coffee price shocks are randomly assigned. Thus, any changes in the proxy of the intensity of coffee growing are not correlated with our measurement of economic activity, once we have controlled for all independent variables.

Other Related Outcomes

We focus in two channels through which international coffee price boom may be affecting the economic activity in Colombian municipalities: schooling and mortality. In the short term, producers in municipalities that were exposed to the coffee price boom may receive more income to their production and they could invest in human capital. For to do that, we estimate our main estimation Equation 3.9 and 3.10 using the average of year education and the mortality rate variable as dependent variable. Especifically, we estimate the following model:

$$C_{mdt} = \alpha_m + \rho_d + \lambda_t + \mu_m \times t + \beta\big(\widehat{Coffee_{md} \times PCoffee_{avt}}\big) + \phi Z_{mdt} + \xi_{mdt} \quad (3.11)$$

The first stage for coffee, is the same implemented in the main estimate:

$$Coffee_{md} \times PCoffee_{avt} = \alpha_m + \rho_d + \lambda_t + \mu_m \times t + \beta(R_{md} \times T_{mt} \times FE_t) + \phi Z_{mdt} + \xi_{mdt} \quad (3.12)$$

In the second stage, Equation (3.11), C_{mdt} could be the average of year of schooling or mortality rates in the municipality i in the year t, instead of night light density. The rest of the specification is equal to that presented in Equation 3.9.

3.5. Data

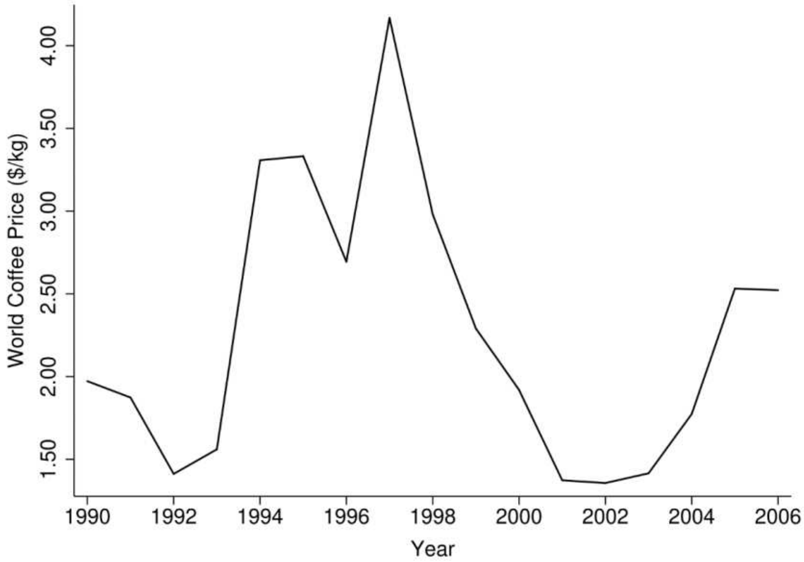
International Coffee Prices

This paper constructs time-series data on the international coffee prices from the International Coffee Organization. The data correspond to the period of 1992 until 2005. The focus of our study is between 1994 to 1997, the period in which the coffee price increased exogenously as a consequence of a frost episode in Brazil that produced a substantial harvest loss.[80] After this episode, prices began to decrease as a result mainly of increased supply from Brazil and Vietnam. In Brazil's case, the increase happened as a result of government policy that stimulated to plant coffee in frost-free areas, which also coincided with the major currency devaluation in 1999. In Vietnam's case, in turn, the supply increases were caused by the normalization of trade relations with the United States and a government strategy to promote the exports which started in 1999. Figure 3.1 shows the time series of average annual international coffee prices.[81] We can visualize the three peaks that we mentioned before. Specifically, focus on our period of study, coffee prices rose dramatically from $1.53 per kilogram in 1993 to a high of $4.17 per kilogram.

[80] There are other episodes of exogenous changes in the international supply of coffee that could be exploited like frosts and drought in Brazil's coffee harvest during 1975 and 1985, respectively; or the collapse of the International Coffee Agreement during 1989-90. Nonetheless, the intensity of night-lights, our key independent variable, is only available from 1992 until 2013.

[81] Figure C.4 in the appendix shows the tendency of internal coffee prices for Colombia from 1990 to 2005. Again, we can observe that between 1994 and 1997 prices increased sharply.

Figure 3.1: Time Serie Internal Coffee Price (1990-2006)



Note: Average annual coffee prices. The data are available at the National Federation of Coffee Growers.

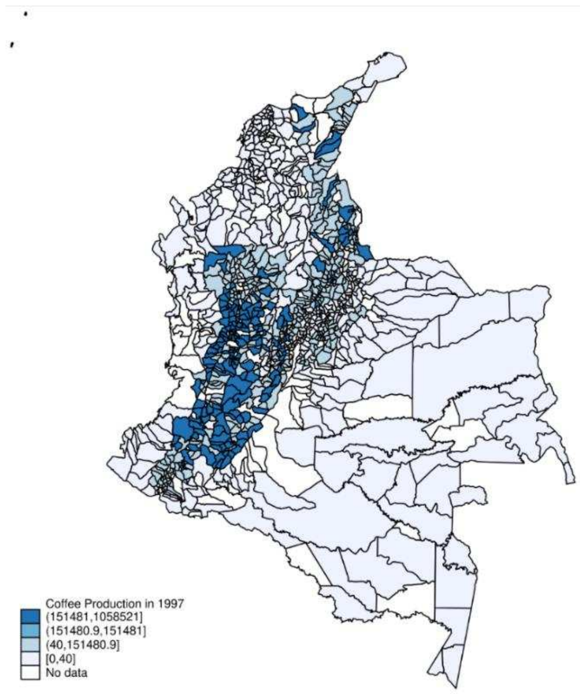
The Intensity of Coffee Production

The National Federation of Coffee Growers (NFCG) had developed three censuses since its creation in 1927: at the beginning of the 70s, at the beginning of the 80s, and the last one at the middle of the 90s.[82] For this study, the measure of the intensity of coffee production is the number of hectares planted with coffee in each municipality in 1997, the most recent data available. We obtained this information from Dube and Vargas (2013). The final sample contains information about 966 municipalities, which correspond to 86% of the total Colombia municipalities. From our sample, 549 municipalities reported producing coffee, which is approximately 57% of our sample. Figures 3.2 and 3.3 draw the geographical distribution of coffee production and the distribution of coffee intensity production at the municipality level in 1997, respectively. Note that although the coffee cultivation is concentrated in the departments of Antioquia, Caldas, Quindío, and Risaralda, there is a significant dispersion among the municipalities, which shows us that the importance of coffee production varies substantially across the municipalities.

[82] The NFCG was born with the purpose to represent Colombia coffee producers both nationally and internationally, as well as to improve the labor conditions and welfare. (See https://www.federaciondecafeteros.org/particulares/en/quienessomosformoredetail:)

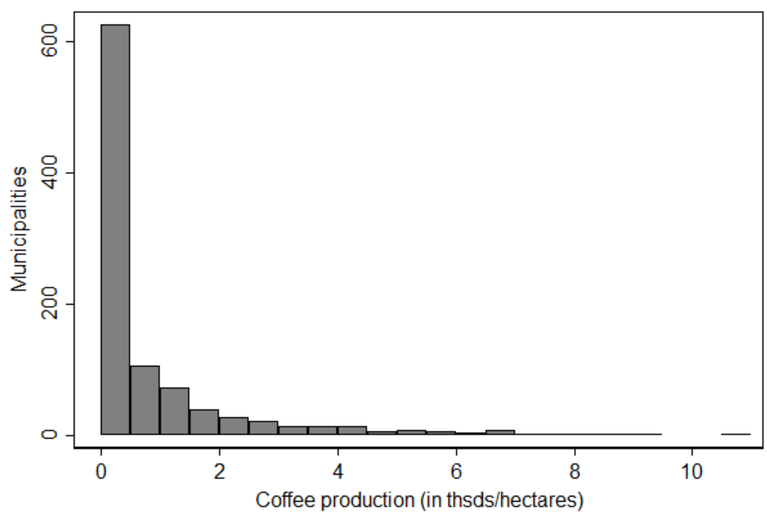
Taken this together, the municipalities are exposed differently to boom and busts in the market given its heterogeneity in intensity in production. Thus, municipalities that are more intensive in production will be more affected by external economic shocks than those less intensive. These characteristics play an important role in our empirical strategy.

Figure 3.2: Geography of Coffee Cultivation in 1997



Note: Author's elaboration based on data from Dube and Vargas (2013).

Figure 3.3: Distribution of Coffee Production



Note: Author's calculation based on data from Dube and Vargas (2013).

Nighttime Light

We use luminosity intensity as our main variable of economic activity across Colombian municipalities. Data came from the Earth Observation Group (EOG) at the National Oceanic and Atmospheric Administration (NOAA). We use data based on Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS). These data are digitally available annually from 1992 to 2013.[83] Satellites are saved in global composite images representing the average of light captured by the OLS sensors. Each satellite observes each place on Earth every night between 8:30 to 10:00 pm local time covering 75°N to 65°S latitude and 180°W to 180° longitude. There are several years in which there are two satellites collecting information on the radiance of light. For these years, we take the data from the two satellites and use the average of them.[84]

The night lights intensity radiance is transformed and saved in a digital number (DN), which ranged from 0 to 63 with a resolution of 30 arc-second area pixels, approximately 0,86 square kilometers at the equator.[85] The data are processed overlaying all daily images obtained during the calendar year removing cloud observations, images modified by sunlight, moonlight, ephemeral lights like lightning and forest fires, and other factors that can affect the artificial lights (HENDERSON; STOREYGARD; WEIL, 2012; ELVIDGE *et al.*, 2003).

Figure 3.4 illustrates graphically how the night-light intensity evolved over Colombia in 1992 and 2005. We can observe that the intensity of the lights increased significantly in many municipalities already illuminated as well as in some municipalities unlit in 1992. In general, the sum of the night-lights intensity rose in mean by 4.09% during this period. We use a raster calculator tool to construct our proxy of GDP. Specifically, we sum up all the digital numbers across pixels for each Colombian municipality for each year.[86]

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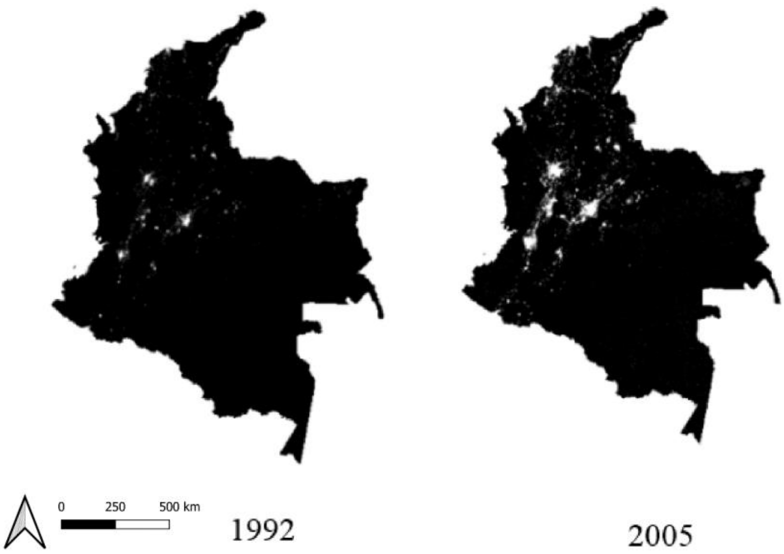
[83] Six sensors have collected this time series of DMSP/OLS nighttime lights for the period of 1992-2013: F10 (1992-1994); F12 (1994-1999); F14 (1997-2003); F15 (2000-2007); F16 (2004-2009), and F18 (2010- 2013).
[84] We also carry out estimation using the luminosity information from the newer satellite as a robustness result.
[85] Note that the luminosity intensity ranking between 0 and 63, where a value of 0 mean no light and 63 the largest luminosity.
[86] Other measures are calculated like mean, median and, the standard deviation of night-lights density. We use these measures in auxiliary regression as robust tests. We also use the inverse hyperbolic since

$$light_{mdt} = \sum_{i=0}^{63} \times (\#\ of\ pixels\ in\ municipality\ m, department\ d, and\ year\ t\ with\ DN = i) \quad (3.11)$$

This measure of night-light intensity has been frequently used to construct indexes over countries and years in this kind of literature. Following Henderson, Storeygard, and Weil (2012), we take the natural log of this sum to construct our main dependent variable.

Figure 3.4: Changes in Night-Lights intensity over Colombia. (1992-2005)



Note: Author's elaboration base on data from NOAA.

Gross Domestic Product (GDP)

As we have mentioned before, the disaggregated national account in developing countries is unavailable or available with poor quality. In Colombia's case, GDP data only are available at national and department levels. We constructed a time series of GDP at the national level from the World Bank from 1992 to 2005. Meanwhile, department GDP data come from Departamento Administrativo Nacional de Estad´ıstica (DANE for its acronym in Spanish), which has been available only since 2000.[87]

(HIS) transformation as an alternative light measure (see e.g. Bruederle and Hodler (2018) for a similar approach).

[87] Data are publicly available at https://www.dane.gov.co/index.php/estadisticas-por-tema/cuentasnacionales/cuentas-nacionales-departamentalespib-base-1994

Census Data

This paper uses microdata from the 1993 Colombian census, the full population census available at the beginning of our period of analysis. The data came from the Integrated Public Use Micro Sample (IPUMS).[88] IPUMS data provide demographic and socioeconomic information about 10 percent of individuals randomly extract to the original census. The information is weighted to preserve representativeness. The Census also provides several socio-demographic characteristics of the population. For our purpose, we construct the average weighted years of schooling, which we use as the dependent variable in our mechanism section. In this exercise, we limit the sample to individuals over 25 years old, because probably their schooling decisions have already finished. On the other hand, we construct the data about the number of households with electricity and water supply and we include it as a control variable in our main results.

Temperature and Precipitation Data

We built a series for temperature and precipitation information using the ERA-Interim data produced by the European Center for Medium-Range Weather Forecasts (ECMWF). ERAInterin data are available at the 0:1 × 0:1 degree latitude/longitude grid. Given that this data is in a finer resolution than our main dependent variable, we use raster calculator tools to construct a time series at the municipality level.[89]

3.6. Results

3.6.1. A first overview of the data.

Table 3.1 displays the descriptive statistics for producing and non-producing municipalities separately. In general terms, our main result variable, which represents the sum of all the pixels within each municipality each year, presents on average, a value of 571.87 for the coffee-producing municipalities, while the average of the non-producers is approximately 984.99. Climatic variables between the two groups are similar. The mean temperature is 21.05 and 21.65 for producers and non-producer respectively.

[88] The IPUMS data are publicly available at https://international.ipums.org/international/
[89] As a robustness test, we use temperature and rainfall data from Dube and Vargas (2013), which is based on climatology station

Table 3.1. Descriptive Statistics

	Municipalities	Observations	Mean	SD	Min	Max
Panel A: Coffee Producer						
Coffee Intensity (in thousands of hectares, 1997)	549	7434	1,52	1,82	0,0004	10,59
Population (in log)	549	7686	-4,35	0,90	-6,76	-1,36
Rainfall (In cm3)	549	7686	1930,79	722,22	300	5910
Temperature (in Celsius)	549	7686	21,05	3,70	11,20	28,90
Internal Coffee Price (in Log)	549	7686	0,56	0,20	0,25	0,93
Top 3 Coffee Producer (in Log)	549	7686	3,49	0,26	3,09	3,84
Light Intensity (Sum of pixels)	549	7685	571,87	903,79	0,19	8122,62
Light Intensity (Mean between Pixels)	549	7685	2,34	5,68	0,00	62,09
Panel B: Non-Coffee Producer						
Coffee Intensity (in thousands of hectares, 1997)	417	5838	0	0	0	0
Population (in log)	417	5838	-4,38	1,03	-8,69	-1,44
Rainfall (In cm3)	417	5838	1809,89	1243,26	160,00	9200
Temperature (in Celsius)	417	5838	21,65	6,21	3,90	28,90
Internal Coffee Price (in Log)	417	5838	0,56	0,20	0,25	0,93
Top 3 Coffee Producer (in Log)	417	5838	3,49	0,26	3,09	3,84
Light Intensity (Sum of pixels)	417	5838	984,99	1882,49	0,99	31097,31
Light Intensity (Mean between Pixels)	417	5838	3,16	7,02	0,01	54,78

Source: Research results.

3.6.2. Relationship between Night-lights and GDP

Several scholars have documented the strong correlation between nightlights and GDP at the national level for a high set of countries (HENDERSON; STOREYGARD; WEIL, 2012; PINKOVSKIY; SALA-I-MARTIN, 2016; MICHALOPOULOS; PAPAIOANNOU, 2013). However, does this relationship exist specifically for Colombia? Is the night-light a good proxy for GDP at the geographic disaggregated level? In this subsection, we investigated these questions and we bring statistical support to the strong relationship plotted in Figures C.1 and C.2 in Appendix C. Specifically, using the OLS estimator, we regressed the log of night-lights intensity on log GDP at the department level. The results are presented in Table 3.2. The corresponding regression yields provide an adjusted r-squared of 0.98 in our preferred specification. Our most basic specification is presented in column (1), where we do not include any controls. In the next specifications, we add controls to the baseline specification. Thus, column (2) adds year fixed effects, column (3) department fixed effects and column (4) department-specific linear time trends.

Overall, the coefficients in columns (1) to (4) suggest a positive and statistically significant linear relationship between log night-lights and log GDP. Furthermore, we can see that the estimated relationship remains very similar in its magnitude across different specifications, although its significance falls from 1 percent in column (1) to 10 percent in the remains. Column (4) provides the elasticity of night-light concerning GDP of 0.283, with a standard error of 0.148. This result is in line with previous studies developed by Pinkovskiy and Sala-I-Martin (2016) who find a coefficient of 0.661 when they do a similar regression of the log light per capita on log GDP per capita. The difference between the coefficients maybe because the analysis of Pinkovskiy and Sala-I-Martin (2016) was carried out at the national level and for various countries, while our analysis is at the subnational level and for a specific country.

Taken together, these results can bring strong support to the hypothesis that the nightlight intensity can be used as a good proxy of economic activity at a more disaggregated level (municipal level, which is the focus of our study). Although these results should be interpreted with caution, since they do not represent a causal effect, they appear to be robust across different specifications.

Table 3.2. Effects of GDP on Night-lights Density

	(1)	(2)	(3)	(4)
Log GDP	0.36193***	0.34192*	0.34192*	0.28337*
	(0.04211)	(0.17049)	(0.17049)	(0.14898)
Year Fixed Effects	No	Yes	Yes	Yes
Department Fixed Effects	No	No	Yes	Yes
Department-Specific trends	No	No	No	Yes
Observations	448	448	448	448
R2	0.965368	0.981515	0.981515	0.986438

Source: Research results.
Notes: The dependent variable is the natural logarithm of the sum of luminosity intensity in department d and year t. Robust standard errors clustered at the department level are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

3.6.3. Effects of Coffee Price Shocks on Night-light Density

Table 3.3 reports the main regression results of the average effects of coffee price shocks on night-lights density. It also shows in detail how the estimated treatment effect varies across different specifications. In the baseline estimation, column (1), we only adjust for demographic characteristics (natural log of population and coca cultivation)[90]. Then, we in each column add a different set of controls. Thus, column (2) adjusted the regression adding region fixed effects, while column adding (3) year fixed effects. Column (4) reveals the estimated coefficient from our preferred specification. This regression incorporates all the control of the first three columns and department-specific linear trends. The estimated coefficient suggests a positive and statistically different from zero effect, which suggests that the night-light intensity of coffee producer municipalities increases more in response to coffee price increases than coffee non-producer municipalities.

To interpret the magnitude of the estimated coefficients, we consider that the coffee boom represented the variation of the natural logarithm of coffee prices between 1994 and 1997 when coffee prices increased by 0.20 log points.[91] We also consider the average coffee intensity of municipalities in 1997, which was 1.52 thousand hectares. Taken this together, the estimated coefficient suggests an increase of 0.014 in the natural log of nightlights density. When we compare this result with the mean of the distribution, this increase reaches up to about 0.26% in the luminosity. This result is in line with the literature that analyzes the effects of exogenous shocks on economic outcomes. For example, Aragón and Rud (2013), studying the local effects of the Yanacocha gold mine in Peru, find that the expansion of the gold mine have a postive effect on population well-being in the short-term. In particular, they show that an increase in 10 percent in the mine's demand for local inputs is associated with 1.7 increase in real income.

[90] Municipalities producing coca (illegal cultivation) may have incentives to change their production to coffee due to the increase in prices of this commodity, which could skew our estimator.
[91] The natural logarithm of coffee price in 1994 was 0.729 while in 1997 was 0.930.

Table 3.3: Effects of Coffee Price Shocks on Night-lights Density

	1	2	3	4
CoffeeProduction1997 × CoffeePrice	0.601***	0.748***	0.189***	0.209**
	(0.029)	(0.031)	(0.027)	(0.094)
Population (in log)	0.249***	0.210***	0.275*	0.335
	(0.046)	(0.050)	(0.161)	(0.250)
Coca Production	0.003	-0.001	-0.004	0.002
	(0.004)	(0.005)	(0.007)	(0.008)
Region Fixed Effects	NO	YES	YES	YES
Year Fixed Effects	NO	NO	YES	YES
Department-Specific trends	NO	NO	NO	YES
Observations	13,271	13,271	13,271	13,271

Source: Research results. Notes: The dependent variable is the natural logarithm of the sum of luminosity intensity in municipality m, department d and, year t. The effect of coffee price shock is computed by multiplying the difference in the log of price from their peak in 1997 { 1994, the coffee intensity (1.52), the estimated coefficient, and dividing the resulting value by the mean of the dependent variable. Robust standard errors clustered at the department level are into parentheses. Following the strategy development by Dube and Vargas (2013), we instrumentalize the interaction of the internal coffee price and coffee production intensity by the interaction of coffee export volume of Brazil, Indonesia, and Vietnam with temperature, rainfall, and rainfall multiplying with temperature.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

3.6.4. Robustness Checks

We have conducted several different specification checks to investigate the robustness of the main finding. As we mentioned above, one might be concerned with confusing the effect of the shock of international coffee prices with changes in the production patterns of coffee growers. If it is a major issue, one would expect to attribute a potential increase in economic activity to increases in production rather than a price effect. It is because producers can change their production preferences once they now have incentives to produce more due to coffee prices being higher. We shed light on this question using data on the coffee intensity of the municipality from the 1980 agricultural census instead of 1997. There is a strong correlation between the intensity of coffee production recorded in the 1980 census and that recorded in the 1997 census. This allows us to deal with any endogeneity that occurs as a result of changes in the producer's behavior producing more coffee due to increases in international prices.[92]

[92] The 1980 coffee census was conducted about one decade before our period of study. Thus, it seems reasonable to assume that this measure is not correlated with our dependent variable in the period studied but is a strong correlation with coffee intensity in 1997.

Table 3.4 shows the results of this exercise. Using the intensity of coffee producer in 1980 produce similar results if we use 1997 census. In particular, we find an estimated coefficient of 0.20 (standard error==0.082), which is statistically significant at the 1 percent level of significance. The magnitude of this coefficient is relatively similar to the baseline model. This result is expected given the high correlation between the two measures of intensity in production.

Table 3.4: Effects of Coffee Price Shocks on Night-light Density (Coffee Intensity 1980)

	1	2	3	4
CoffeeProduction1997 × CoffeePrice	0.722***	0.788***	0.209***	0.204**
	(0.040)	(0.026)	(0.056)	(0.082)
Population (in log)	0.312***	0.356***	0.345	0.335
	(0.046)	(0.050)	(0.061)	(0.350)
Coca Production	0.003	-0.001	-0.004	0.002
	(0.006)	(0.005)	(0.005)	(0.005)
Region Fixed Effects	NO	YES	YES	YES
Year Fixed Effects	NO	NO	YES	YES
Department-Specific trends	NO	NO	NO	YES
Observations	13,271	13,271	13,271	13,271

Source: Research results. Notes: The dependent variable is the natural logarithm of the sum of luminosity intensity in municipality m, department d and, year t. The effect of coffee price shock is computed by multiplying the difference in the log of price from their peak in 1997 - 1994, the coffee intensity from 1980, the estimated coefficient, and dividing the resulting value by the mean of the dependent variable. Robust standard errors clustered at the department level are into parentheses. Following the strategy development by Dube and Vargas (2013), we instrumentalize the interaction of the internal coffee price and coffee production intensity by the interaction of coffee export volume of Brazil, Indonesia, and Vietnam with temperature, rainfall, and rainfall multiplying with temperature.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level

3.7. Other Related Outcomes

As shown in the previous section, there is a strong and positive relationship between the shock coffee prices and night lights intensity. Nevertheless, what is behind this relationship? In this section, we try to answer this question by investigating other economic outcomes that could also be affected by the coffee price boom. Specifically, we estimate the specification showed in Equation (3.11) and (3.12) using as dependent variable the average of year of schooling and mortality rates. Again the variables are transformed using natural logarithm, in which the estimated coefficient can be interpreted as elasticities due to our price shock variable are measured in terms of log points also. Table 3.5 shows the results of this exercise. More specifically, the estimated coefficient suggests a positive effect of the price coffee shock on years of education and a negative effect on mortality. These results can be interpreted as a better economic condition in coffee producer municipalities after the increase of international coffee prices. Thus, municipalities that are affected by the price boom could have higher salaries, due to the unexpected increase in their income, which could cause an increase in private investment in education, which would improve schooling levels in medium and long-term. These findings are consistent with some pieces of literature that show that better economic condition reflected in more school resources have a positive effect on years of education (CASE; DEATON, 1999; DUFLO, 2001; PAXSON; SCHADY, 2002; CARD; KRUEGER, 1996).

For the Colombian case, Mejía (2020), analyzing the boom in the gold mining sector, finds that enrollment in primary school increases while school dropout decreases. Nevertheless, the author documents a decline in the quality of learning. Specifically, after the price boom, students located in mining areas show decreases in the performance of standard tests. A little different with this result, Santos (2018), also studying the boom in gold sector, shows that the boom in the gold sector reduces the attendance of children in school. In particular, he find that gold boom increase the probability that child works in 9.3% and as consecuence the school attendance descreces around 23.9%. Although Santos (2018) and Mejía (2020) analyze a sector different from ours and take early childhood education compared to our work that considers the total years of schooling, our results differ slightly from the findings of these authors.

Table 3.5: Effects of Coffee Price Shocks on Schooling and Mortality

	Year's of Schooling	Mortality
CoffeeProduction1997 × CoffeePrice	0.001*	-0.021***
	(0.060)	(0.026)
Population (in log)	0.032***	0.256**
	(0.046)	(0.050)
Coca Production	0.002	-0.001
	(0.016)	(0.022)
Region Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Department-Specific trends	YES	YES
Observations	13,271	13,271

Source: Research results. Notes: The dependent variable is the natural logarithm of the years of schooling or mortality data in municipality m, department d and, year t.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

3.8. Conclusion

This paper has offered new evidence on the effects of macroeconomic shocks on local economic activity in a developing country. For this purpose, we have used a novel measure of local economic activity. Specifically, we have used data of satellite images on light density at night as a proxy of GDP. This question is particularly important in developing countries where shock in commodities prices has an important influence on the local economic activity and often data at the sub-national level are not available or are plagued with measurement errors. Thus, we can obtain a more accurate measure of local economic activity that allows us to have a better understanding of the welfare of the population.

We advance in the understanding of how changes in environmental economics affect the local economic activity. For that, this paper exploits the boom of coffee that Colombia experienced within the middle of the 90s to explain the economic activity measured as the intensity of artificial light at night. Using a difference-in-difference as an empirical approach, our estimates provide two important results. First, we identified that coffee producer municipalities' experienced a differential and statistically significant increase in the night-lights density compared to non-coffee producer municipalities. Our main estimate provides an elasticity in coffee price shock of 0.20 that can be understood as an increase of 0.26% in the natural log of night-lights density if we compare with the respective mean of the distribution. Second, we provide a new proxy of GDP at the municipality level that could be useful for future research once data are not available for this country.

Appendix C

Figure C.1: Relationship Night Light and Colombia GDP at National Level

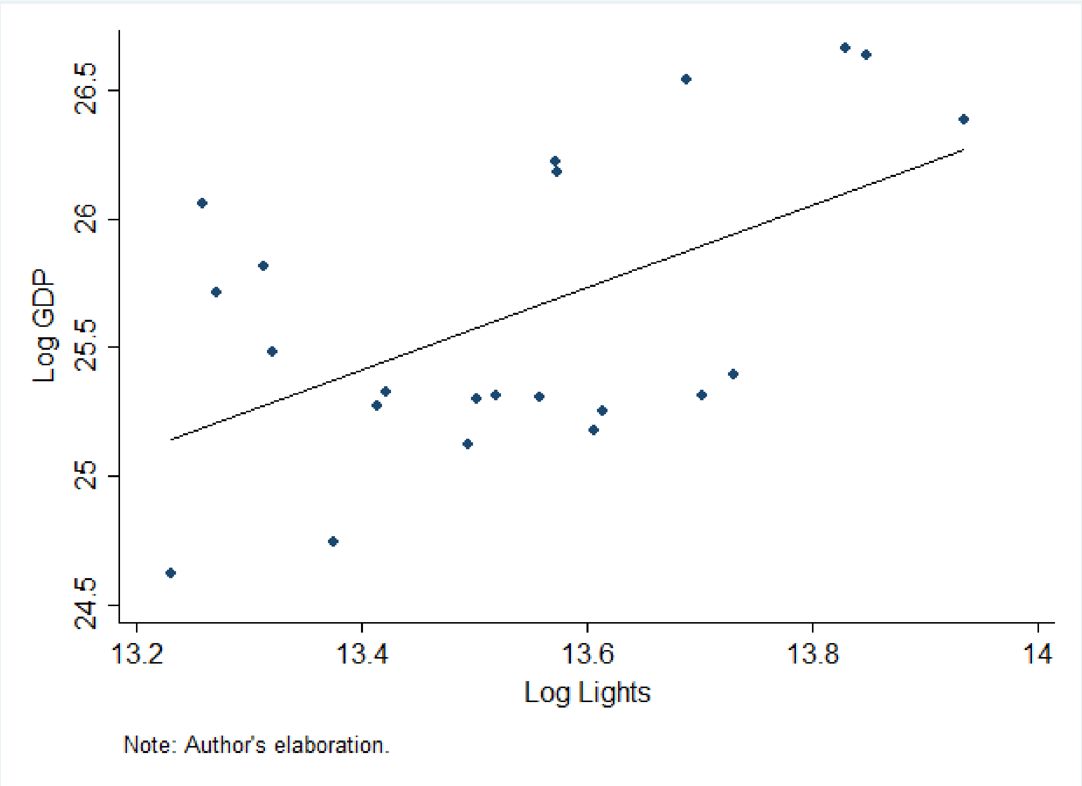


Figure C.2: Relationship Night Light and Colombia GDP at the Department Level

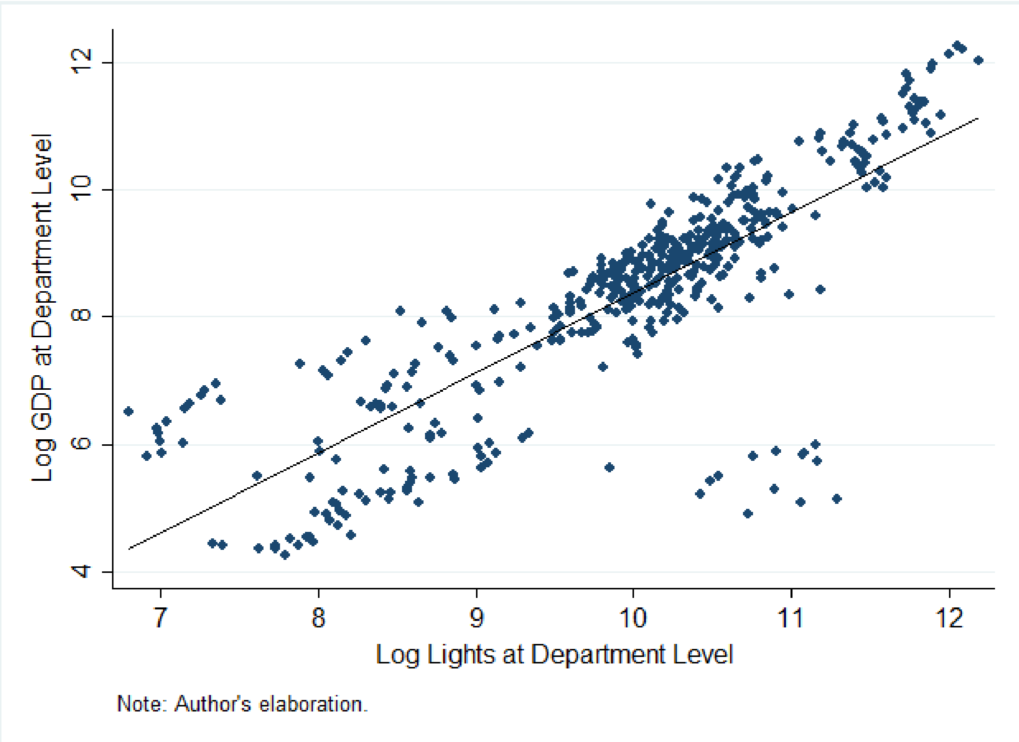
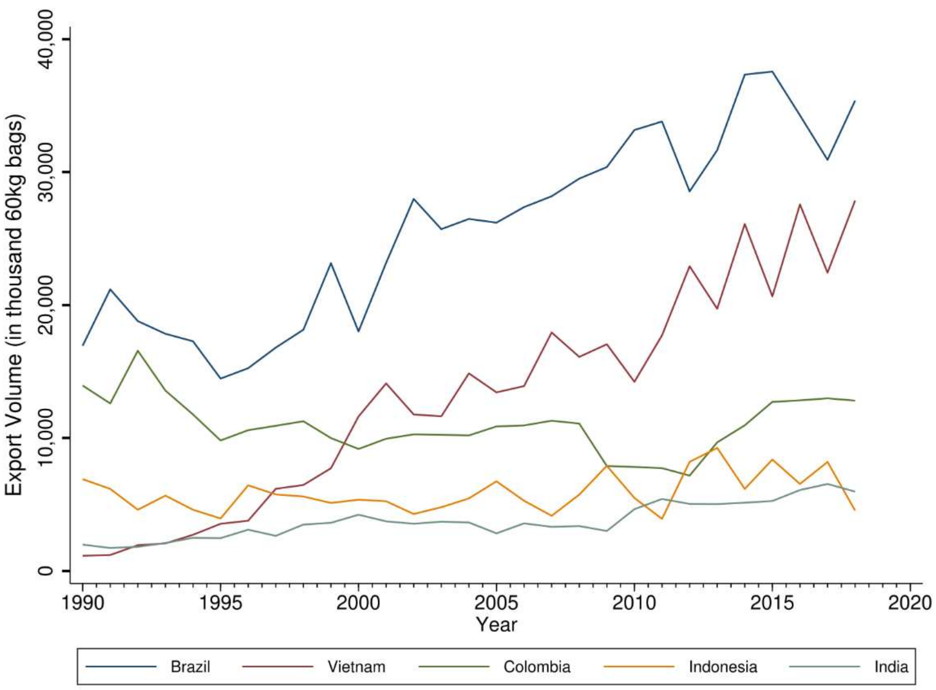
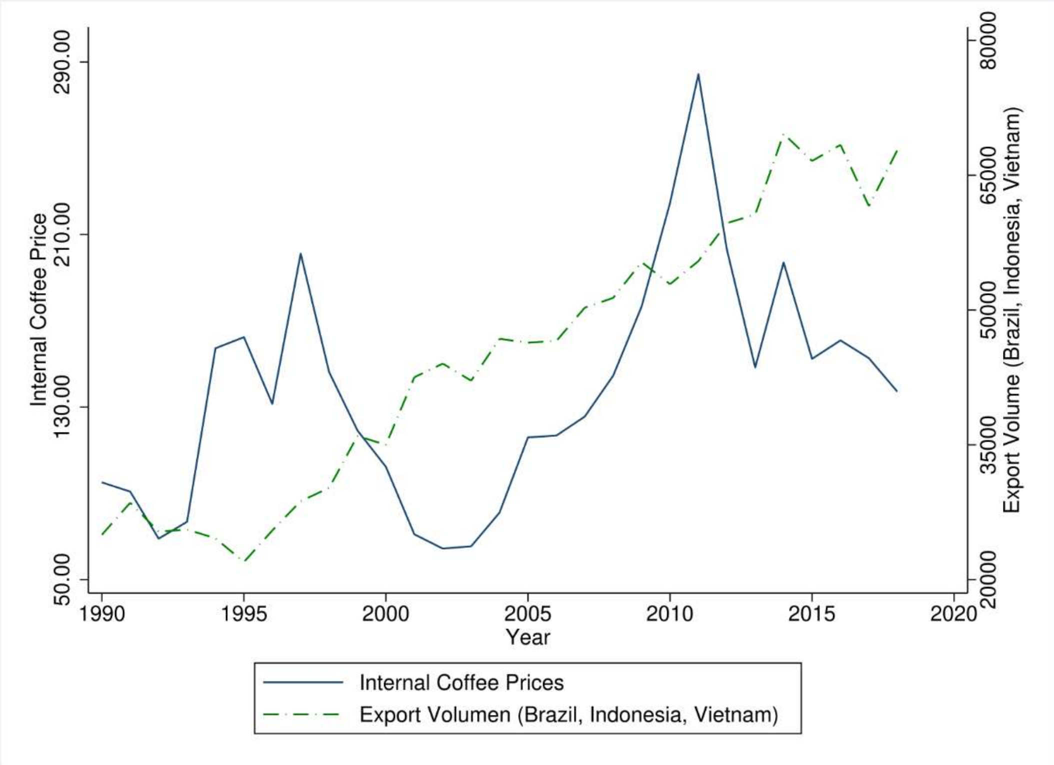


Figure C.3: Export Volume Top 5 Coffee Exporter Worldwide



Note: Author’s elaboration base on data of International Coffee Organization

Figure C.4: Relationship Between Internal Coffee Price and Export Volume of Brazil, Indonesia, and Vietnam



Notes: Author's elaboration base on data of International Coffee Organization and the National Federation of Coffee Growers of Colombia.

Final Remarks

This thesis discussed three questions of development economics. We have proposed a new variable as a proxy for economic activity different from those used in the traditional literature. Using night lights as a proxy for economic activity, we have documented how unexpected economic price shocks, how institutional policies and how infrastructure programs have effects on economic activity at the local level. Specifically, in the first chapter, we evaluated the impact of an environmental policy in Brazil – The Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) – on the economic activity at dessagregate level. Starting in 2004, the PPCDAm aimed to reduce the high rates of deforestation that Brazil was experiencing. Quickly, the policy took effect and the rate of deforestation fell from about 27772 in 2004 to 4571 square kilometers in 2012. As part of the economic activity in this area is related to illegal deforestation, one might expect that along with the drop in the deforestation rate the economic activity would also be affected. However, our results from difference-in-difference approach show that there is only a slight drop in economic activity in the fourth year after the implementation of the policy in the municipalities within the legal Amazon compared to the rest of the Brazilian municipalities. Then, we have taken a different point of view and used a regression discontinuous approach to compare areas within Brazil with areas outside the Brazilian territory. Considering bandwidths of 1 and 5 kilometers, we do not find statistical difference in the density of light in pixel inside and outside Brazil. Nevertheless, using a 100 kilometers bandwidth, we found that before the policy the growth rate of luminosity in the Brazilian territory was relatively higher than that of its neighbors while one year after the implementation of the policy, the growth rate became negative and subsequently became statistically insignificant.

Second chapter documents the relationship of transportation infrastructure on economic activity in Brazil. We take advantage of a natural experiment, the creation of Brasilia – the Brazil new capital and estimate the long lasting effects on economic outcomes. The construction of Brasilia in the 1960s was from scratch, in an uninhabited area and not connected to the rest of the country. Thus, there was a need to connect the new capital with the main population and economic centers of the country. A new road network was built which connected the main cities but also connected areas that were encountered along the way. Our results reveal that microregions closer to the highway present better economic activity measures as the night light intensity than microregions far away.

Last, in chapter 3, we study the effects of the coffee price shock on the Colombian municipalities economic activity. To do that, we use the variation in international coffee price interacted with the geographic distribution of coffee production across Colombian municipalities. In sum, the results indicate that coffee price boom have a positive effects on economic activity in coffee producing municipalities in Colombia compare with non-producing municipalities. Taken these results together, night lights show that they can be used as a proxy for economic activity in different contexts, especially at a disaggregated level where there is often no precise information on economic activity.

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