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Growth, Nighttime Lights and Power Infrastructure Investment: Evidence from Angola

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Growth, Nighttime Lights and Power Infrastructure Investment: Evidence from Angola*

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Abstract

An increasing number of papers in the literature use satellite data on nighttime lights as a proxy for economic activities, such as GDP or GDP growth. They implicitly assume that the relationship between GDP and nighttime lights works through the demand side, and there is no constraint on the supply of electricity. This paper first points out a paradox in using this method: the countries for which the method is needed the most, i.e. the countries with poor statistical capacity, are just the countries, for which the assumption of the method is satisfied the least, i.e. the countries with a large power infrastructure deficit. Motivated by this, we collected the data on power infrastructure investment in Angola, a country with a large power infrastructure funding gap. Indeed, we find that in the case of Angola the stable relationship between GDP growth and lights growth assumed in the literature is broken. Instead, increase in lights strongly co-moved with increase in power infrastructure investment. The strong link between lights and investment enables us to develop a new method of quantitatively evaluating value-for-money for infrastructure investments, which directly estimates the cost-effectiveness of transforming investment to welfare, as measured by lights. We estimate the overall cost-effectiveness, and the cost-effectiveness of different financing methods in the case of Angola.

JEL classifications: Q4, O1, H4
Keywords: growth accounting, nighttime lights, investment, electricity, infrastructure, value-for-money

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1. Introduction

In the literature, a number of existing papers have estimated the relationship between luminosity observed from satellites and GDP or GDP growth using cross-sectional data or panel data and then used the estimated relationship to infer GDP or GDP growth for countries with unreliable national accounts data. In addition to the national level, the method has also been used to infer economic activity at the subnational or supranational level where economic statistics are not available (Croft, 1978; Elvidge et al., 1997; Sutton and Costanza, 2002; Ebener et al., 2005; Doll, Muller and Morley, 2006; Sutton, Elvidge and Ghosh, 2007; Ghosh et al., 2009, 2010; Henderson, Storeygard and Weil, 2012). The crucial assumption in these papers is that there is a stable relationship between GDP and observed lights, such as in Elvidge et al. (1997), or between GDP growth and the growth of observed lights, such as in Henderson, Storeygard and Weil (2012). That is, they implicitly assume that the relationship works through the demand side, and there is no constraint on the supply of electricity, such that both supply and demand adjust smoothly to reflect wider economic development.

However, this assumption may be problematic in countries with poor power infrastructure, where it is unlikely that increased incomes and consumption in the economy as a whole will be converted smoothly into increased power consumption, and hence light emissions. This is because for these countries with poor power infrastructure, nighttime lights are constrained by the capacity of existing infrastructure and are not by the demand of electricity. As a result, there is no stable relationship between GDP (or its growth) and lights (or their growth). Instead, increases in lights is only possible through investments in power infrastructure and other power sector activities such as reforms. This is especially the case for countries with unreliable national accounts data.

Table 1 shows the status of power infrastructure in the 30 countries that are classified as bad data countries in Henderson, Storeygard and Weil (2012) as their statistical capacities are rated by the World Bank between 0 and 3 (out of 10). Given their poor statistical capacity, these countries are where the above method of estimating GDP (or GDP growth) using nighttime lights data is supposed to be most useful. However, we can see that these countries are also the countries with a lot of power infrastructure deficits. Electrification rates, i.e. percentage of population with access to electricity, are on average 43% and can be as low as 7% in Burundi. On average, 45% of firms have identified electricity as a major constraint and 4.71% of annual sales have been lost due to electrical outages. With these poor power infrastructure and the resulting constraint on the supply of electricity, the assumed stable relationship between GDP (or its growth) and nighttime lights (or their growth) will be broken. Furthermore, given the huge variations in power infrastructure deficits across these bad data countries, it appears problematic for a stable lights-GDP interpretation to be applied, without correcting for power sector particularities.

Table 1: Power Infrastructure for Countries with Unreliable National Accounts Data

Country	Electrification Rate (%)	% of Firms Identifying Electricity as a Major Constraint	Losses Due to Electrical Outages (% of Annual Sales)
Angola	37	36	8.8
Burundi	7	47	2.6
Benin	38	56	3.1
Burkina Faso	13	54	3.2
Central African Republic	11	76	22.1
Cote d'Ivoire	56	40	2.2
Cameroon	54	59	4.3
Congo, Rep.	42	71	9.6
Algeria	100	48	1.6
Eritrea	36	0	0
Ghana	64	61	11.4
Gambia, The	35	78	9.8
Guinea-Bissau	61	74	2.5
Haiti	38	NA	NA
Iran, Islamic Rep.	100	NA	NA
Lebanon	100	55	5.7
Liberia	10	59	0.8
Madagascar	15	26	6.8
Mali	26	34	1.1
Myanmar	52	24	2.1
Mauritania	22	58	1.2
Niger	14	63	1.1
Nigeria	56	48	10.8
Oman	98	NA	NA
Rwanda	18	15	1
Sudan	33	8	1.1
Sierra Leone	14	53	5.5
Swaziland	42	12	1.6
Vietnam	99	7	1.1
Congo, Dem. Rep.	16	52	6.2
Average	43	45	4.7

Source: WDI and Enterprise Surveys.

Motivated by the fundamental role played by power infrastructure in the relationship between GDP and lights, we collected the data on power infrastructure investment in Angola, a country with a large power infrastructure deficit, and show that in the case of Angola there is no significant statistical relationship between GDP growth rate and lights growth but increase in lights strongly co-moved with infrastructure investment. The strong link between lights and investment enables us to develop a new method of quantitatively evaluating value-for-money for infrastructure investments, which directly estimates the cost-effectiveness of transforming investment to welfare, as measured by lights. In the literature, traditional methods of evaluating value-for-money only compare investment costs. For example, the government may have built a project using a particular financing method. Ex-post, the government would conjecture what the cost would be if the same project had been built using other financing methods. Then the government compares the actual cost with the conjectured cost to see which method gives the most value for money. However, this method is subject to two problems. First, as the construction company may also be responsible for the design of the project and hence has an incentive to build an unnecessarily large project, we could end up with a white elephant project. The second problem is that although the project may be built according to the blue print, there is still a lot of uncertainty about quality, which is only observable ex-post. But with out method, we can quantitatively evaluate those ex-post observable quality indicators.

The new method can not only be used to quantitatively evaluate value-for-money for power infrastructure investments in general, it can also be used in the context of Angola to address the fundamental economic problem for resource rich developing countries: How to transform natural resources to other assets, such as infrastructure, that can benefit their citizens and generate sustained long term growth (van der Ploeg and Venables, 2012). This is especially true for African resource rich economies, as their underdeveloped infrastructure has been a major obstacle for development. For example, in oil rich countries, such as Nigeria, Angola and Sudan, the 2010 rates of access to electricity were only 50.3%, 40.2% and 35.9% respectively. In addition, frequent power outages are also common and lead to big loss in sales for firms. For instance, firms in Angola lost 12.6% of their sales in 2010 and Nigeria lost 8.9% in 2007 due to electricity outages.[1] The under-development in power infrastructure has been mainly caused by lack of funding. Although domestic public finance is still the largest source of funding for infrastructure, much more are needed. This is because despite the recent rapid economic growth, the increase in the flows of internal finance cannot keep up with the ever increasing infrastructure demand, as a result, Africa's infrastructure gap has widened. And the funding gap in the power sector is by far Africa's largest infrastructure challenge. To fill the funding gap, African countries have to rely on alternative sources of finance.

Traditionally, external sources of finance for infrastructure in Africa were mainly the official development assistance (ODA) from OECD countries and public-private partnership (PPP). However, during the past decade non-OECD financiers has been playing an increasingly important role in financing infrastructure in Africa. China is the major player among non-OECD financiers, providing loans that are mainly resource-backed through the Export-Import Bank of China.

Although the available financing methods have made and will make significant contribution to fill the funding gap, due to the different features associated with each

[1] World Development Indicators (WDI).

financing method, such as corruption and tiedness, different financing methods vary in their effectiveness of converting the same amount of funding into welfare. Therefore, understanding the effectiveness of different financing methods is a matter of importance and urgency. Of course countries may choose a financing method for reasons that are other than cost-effectiveness, but it is still important to know which financing method is the best in terms of value-for-money in the first place. This paper answers the question by comparing different financing methods in terms of their effectiveness of transforming infrastructure investment into welfare. The financing methods to be compared include internal finance (IF), official development assistance from OECD countries (ODA), public private partnership (PPP) and resource-backed loans mainly from China (RBL).

Our empirical methods overcome two difficulties in comparing the effectiveness of investments. First, ideally we would like to measure welfare increase as a result of a power infrastructure project by power consumption increase. However, data on power consumption at the disaggregated level is not available in Angola. Due to the strong relationship between power consumption and luminosity from the DMSP/OLS nighttime lights data found in the literature (Elvidge et al., 1999), we use the increase in luminosity in DMSP/OLS in the areas that can be affected by a new power infrastructure project as a proxy of the resulting power consumption increase. The use of nighttime lights data is more cost-effective compared with other data collection methods. Second, estimating the effectiveness of transforming infrastructure investments to power consumption across financing methods is subject to selection bias. Just like in the estimation of return to education, the observed return needs to be corrected for self-selected occupational or migration choices, the observed effectiveness of investments also needs to be corrected for the selection of financing methods. For example, the financier of a financing method may have a strong preference to fund the projects close to natural resources in order to take advantage of the resource boom. In this case, without correcting the selection bias, the effectiveness of this financing method will be upward biased. In the case of this paper, our selection model is a truncated selection model with polychotomous choices. In the literature, a series of methods have been proposed to deal with it, such as Lee (1983), Dubin and McFadden (1984) and Dahl (2002). In this paper, we model the selection of financing methods as multinomial logit model, which depends on project size, distance to natural resources, distance to land mines and infrastructure type. We then simultaneously estimate the selection equation with the outcome equation describing the effectiveness of investments using the methods summarized in Bourguignon, Fournier and Gurgand (2007). This paper finds that without correcting the selection bias, all financing methods are significantly effective, i.e. projects financed by these methods significantly increase the power consumption.

In terms of the order of effectiveness, PPP is the most effective method, which is followed by RBL. And ODA and IF rank third and fourth respectively. After correcting the selection bias, RBL becomes the most effective, which is followed by IF. And ODA and PPP are less effective than the other two methods.

The rest of the paper is structured as follows. Section 2 uses cross-sectional and panel data evidence to show the role played by power infrastructure in the relationship between GDP and lights. Section 3 provides background information about the electricity sector and the typical decision process for electricity infrastructure investments. Section 4 describes the data. The general empirical strategies are set out in Section 5. Section 6 presents the empirical results. Section 7 concludes.

2. The Relationship between GDP, Nighttime Lights and Power Infrastructure

Measurements using satellite data on nighttime lights are becoming increasingly widespread as a proxy method for evaluating economic activities, such as GDP or GDP growth. The crucial assumption in these papers is that there is a stable relationship between GDP and observed lights, such as in Elvidge et al. (1997), or between GDP growth and the growth of observed lights, such as in Henderson, Storeygard and Weil (2012). That is, they implicitly assume that the relationship works through the demand side, and there is no constraint on the supply of electricity, such that both supply and demand adjust smoothly to reflect wider economic development. However, in the countries where light data is being most widely relied upon - those developing countries with a paucity of accurate economic statistics - are often countries with the largest electricity supply constraints. Therefore, the stable relationship between lights and GDP may not hold in this supply-constrained context. To investigate the role played by power infrastructure in the relationship between GDP and lights, we replicate the estimations of Henderson, Storeygard and Weil (2012) using the same dataset, supplemented by information on country-specific power sector constraints, as measured by the electrification rate in 2000. Table 2 first shows the cross-sectional evidence on the relationship between lights, GDP and power infrastructure in 2000. (1) shows that there exists a significant positive relationship between the log of lights and the log of GDP. However, when controlling for electrification rate, the estimated coefficient for the log of GDP is not significant anymore, but that of electrification rate is significantly positive. Moreover, R-squared increases significantly from 0.164 in (1) to 0.585 in (2). In (3) we test how the GDP-lights relationship varies with electrification rate. The estimated coefficient of the log of GDP is significantly negative, but the interaction term of electrification rate and the log of GDP is significantly positive. This implies that the relationship between lights and GDP depends on power infrastructure. It is only possible to get a positive relationship between them when the electrification rate is high.

Table 2: Lights-GDP Relationship Using Cross-sectional Data in 2000

Independent Variable	(1) ln(lights/area)	(2) ln(lights/area)	(3) ln(lights/area)
ln(GDP)	0.345***	0.0388	-0.126**
	(0.0590)	(0.0476)	(0.0551)
Electrification Rate(2000)		0.0452***	
		(0.00341)	
ln(GDP)$\times$ Electrification Rate(2000)			0.00198***
			(0.000151)
Constant	-8.149***	-4.146***	-0.435
	(1.406)	(1.038)	(1.158)
Observations	177	177	177
R-squared	0.164	0.585	0.581

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 shows the pooled OLS esimats for the relatoinship between lights levels and levels of GDP. (1) shows that without controlling for power infrastructure, there exists a significant linear relationship between the log of lights and the log of GDP. However, the hypothesis that the slope coefficients are the same across countries is rejected, as shown in Panel B. When controlling for power infrastructure as measured by electrification rate in 2000, the estimated coefficient of the log of GDP is not significant anymore, but the estimated coefficient of electrification rate is significantly positive. Further, R-squared increases significantly from 0.166 in (1) to 0.589 in (2). In (3), instead of being included as an intercept, electrification rate interacts with the log of GDP and the estimated coefficient for the interaction term is significantly positive, which implies that the relationship between GDP and lights is more positive when the electrification rate is higher. This explains why the hypothesis that the slope coefficients are the same across countries is rejected. The estimated coefficient of the log of GDP is significantly negative. This implies that we could not expect a positive GDP-lights relationship when the electrification rate is very low. The same results hold when these regressions are run using panel data with random effects, as shown in Table 4.

Table 3: Lights-GDP Relationship Using Panel Data from 1992-2008 (Pooled OLS)

Independent Variable	(1) ln(lights/area)	(2) ln(lights/area)	(3) ln(lights/area)
Panel A:			
ln(GDP)	0.338***	0.0389	-0.124**
	(0.0540)	(0.0496)	(0.0577)
Electrification Rate(2000)		0.0451***	
		(0.00329)	
ln(GDP)$\times$ Electrification Rate(2000)			0.00198***
			(0.000145)
Constant	-8.422***	-4.612***	-0.947
	(1.339)	(1.072)	(1.215)
Year FE	Yes	Yes	Yes
Observations	2,909	2,909	2,909
R-squared	0.166	0.589	0.586
Panel B:			
F-test of H_0: Slope Coefficients are the same for all countries (P-value)	< 0.01		

Robust standard errors clustered by country are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Lights-GDP Relationship Using Panel Data from 1992-2008 (Random Effects)

Independent Variable	(1) ln(lights/area)	(2) ln(lights/area)	(3) ln(lights/area)
ln(GDP)	0.485***	0.299***	0.234***
	(0.0683)	(0.0572)	(0.0620)
Electrication Rate(2000)		0.0433***	
		(0.00401)	
ln(GDP)$\times$ Electrication Rate(2000)			0.00130***
			(0.000188)
Constant	-12.48***	-10.96***	-8.572***
	(1.762)	(1.522)	(1.435)
Year FE	Yes	Yes	Yes
Observations	3,015	3,015	3,015
R-squared	0.005	0.354	0.267
Panel B:			
F-test of H_0: Slope Coefficients are the same for all countries (P-value)	< 0.01		

Robust standard errors clustered by country are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

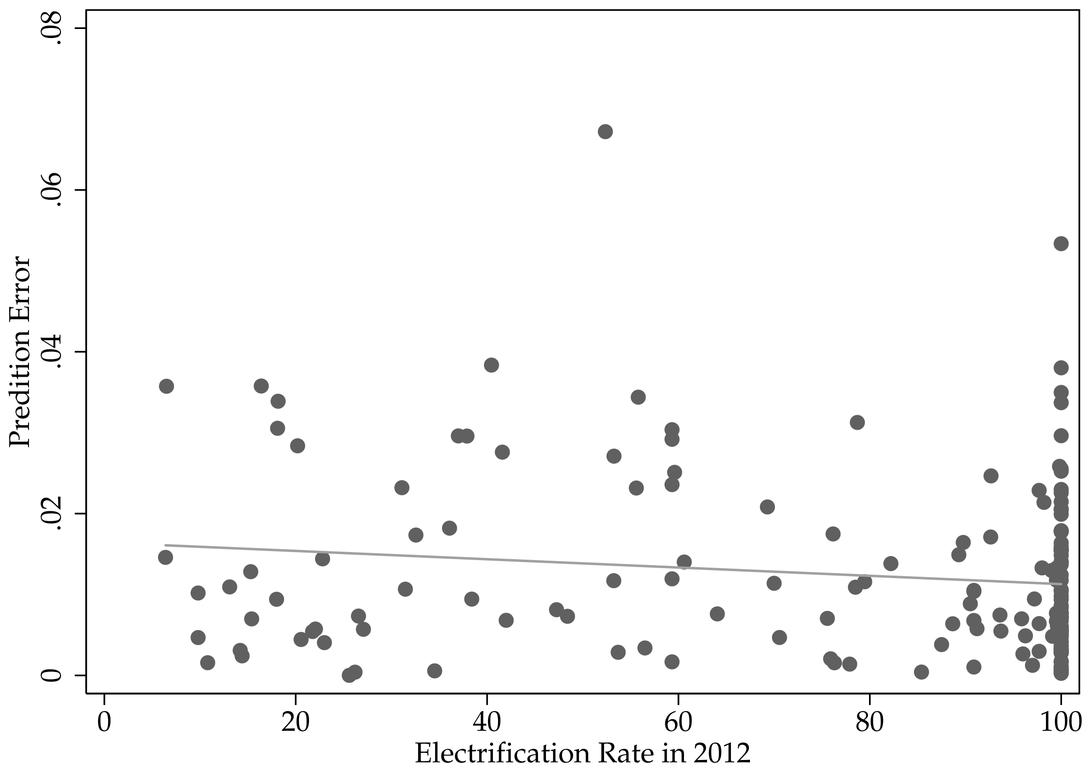
The implication of this is that data on power infrastructure can be used to help estimate GDP (or its growth). For example, the method described in Henderson, Storeygard and Weil (2012) could be augmented with data on power infrastructure as the prediction errors from their paper, the difference between the predicted annualized percentage change in GDP from lights and the annualized percentage change in GDP, are significantly negatively correlated with electrification rate in 2012 (Figure 1).

Given the important role played by electrification rate in the relationship between GDP and lights, we propose to examine detailed power sector investment data for Angola, where granular data on the infrastructure type, investment value and financing source of these investments allows us to further investigate the relationship between lights, GDP and power infrastructure.

3. Background on the Electricity Sector

Electricity infrastructure investments are usually planned well beforehand to meet the future demand of electricity. In Angola, the typical decision process of the government involves a two-step procedure. In the first step, a government agency uses a least-cost power generation expansion model to calculate the technical specifications of the electricity infrastructures that need to be built in order to meet future electricity demand.

Figure 1: Prediction Error and Electrification Rate



In the second step, the government then decides which type of methods to be used to finance the infrastructures taking into account the different features of each method.

3.1. The Least-Cost Power Generation Expansion Model

In Angola, around every five years, the government usually makes a plan of power infrastructure investment for the following years in order to meet the expected demand of electricity. To do so, the government first uses historical data on regional power consumption and economic growth to estimate the relationship between the two. Then the future regional power consumption can be forecasted using the estimated relationship and forecasts of future economic growth. Next, a least-cost expansion linear programming model is used to minimize the total cost of producing and distributing electricity to meet the forecasted electricity demand. The total costs involve all the costs occurred in the electric system as shown in Figure 2, including production as well as investment and refurbishment costs for generation, and investment, refurbishment and operation costs of transmission lines and distribution networks. Using these steps, the government can then decide what generating plants, transmission lines and substations to be built in the next few years and their estimated costs.

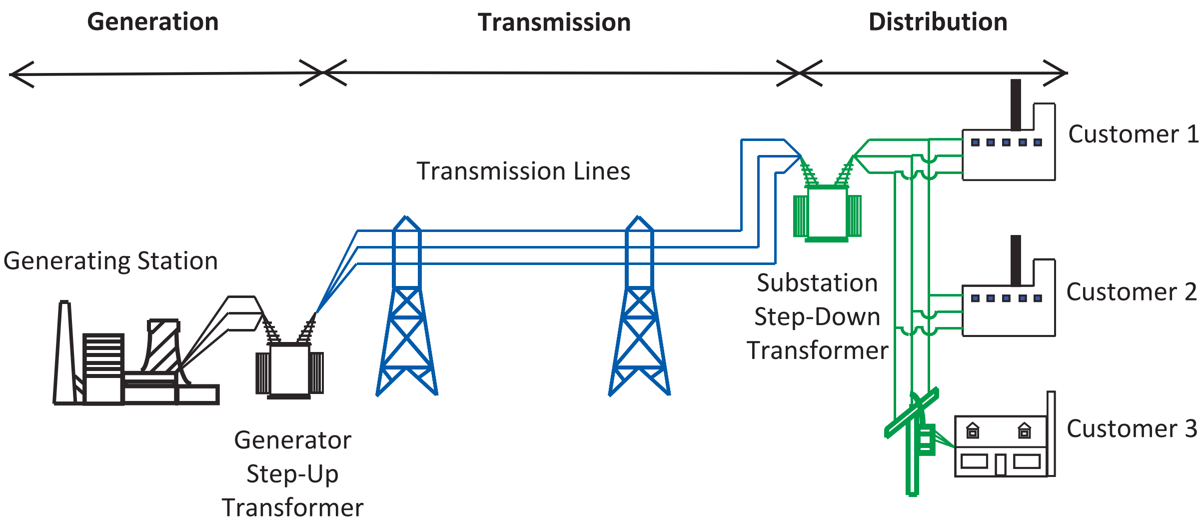


Figure 2: Basic Structure of the Electric System

3.2. *The Choice of Contract Type*

After the technical specifications are decided, the government will then decide what types of contracts to be used for each project. Currently, there are four major financing methods used in Angola, including ODA, PPP, resource-backed loans and internal finance. The detailed features and the cost-effectiveness factors (tiedness and corruption) of each method are listed as follows:

3.2.1. *Official Development Assistance (ODA)*

The Development Assistance Committee of OECD (DAC) defines ODA as those flows to countries and territories on the DAC list of ODA recipients and to multilateral institutions which are:

1. provided by official agencies, including state and local governments, or by their executive agencies; and

2. each transaction of which:

(a) is administered with the promotion of the economic development and welfare of developing countries as its main objective; and

(b) is concessional in character and conveys a grant element of at least 25 percent (calculated at a rate of discount of 10 percent).

In terms of ODA's tiedness, it is in general partially tied. However, there has been recently an increasing trend for the proportion of untied aid and the proportion has risen from 46% in 1999-2001 to 82% in 2008 (Clay, Geddes and Natali, 2009).

In addition to tiedness, another important factor of ODA's effectiveness is corruption, especially when the aid is channeled through the recipient countries. Corruption related to ODA is not rare in the news. However, it is difficult to quantify the general picture as it is hard to differentiate corruption from other types of inefficiencies.

3.2.2. *PPP*

Investment in infrastructure is usually not financially viable from a private sector perspective. It is usually believed that infrastructure projects in Africa normally need at least 20% profit to make private firms to invest in them. Even for the projects that are financially viable for private firms, due to market imperfections, infrastructure produces positive externalities and private firms, which act in their own best interest, will underinvest in infrastructures from the society's perspective. Therefore, private-participation in infrastructure is usually in the form of public-private partnership (PPP).

The main characteristic of a PPP, compared with conventional provision, is that it bundles investment and service provision in a single long-term contract. For the duration of the contract, which typically lasts several decades, the private firm manages and controls the assets, usually in exchange for user fees and government transfers, which compensate for investment and other costs. At the end of the contract, the assets revert to government ownership. Compared with internal finance, it is generally believed that PPP can, to some extent, relieve government's budget. In addition, as finance, investment, and management is delegated to private firms, PPP is usually more efficient.

In general there are many types of contracts for private participation. In this paper, we will focus on only the contracts that involve infrastructure investments, such as concession and greenfield projects[2], as for these projects we can easily identify the cost, i.e. the investment, and the outcome, i.e welfare improvement. And contracts such as lease and management contracts that do not include infrastructure investments are excluded. [3]

In terms of cost-effectiveness, PPP is generally untied. In addition, as it is a contract between private firms and government, it could also involve corruption.

3.2.3. *Resource-Backed Loans*

In addition to lower interest rates and longer repayment periods, the distinguishing feature of Chinese resource-backed loans is that the repayment is guaranteed by the

[2]In the case of concession, a private company enters into an agreement with the government to have the exclusive right to operate, maintain and carry out investment. Greenfield projects are new projects usually built and operated by the private sector, which takes on the commercial risk. Such projects can take many forms, but the most common is Build-Operate-Transfer (BOT).

[3]A lease contract gives a company the right to operate and maintain a public utility, but investment remains the responsibility of the public. Under a management contract the operator will collect the revenue only on behalf of the government and will in turn be paid an agreed fee and also does not take responsibility for investment.

sale of a certain amount of natural resources, such as oil (e.g. normally set in barrels of oil per day), throughout the loan repayment period to a specified Chinese National Oil Company (NOC), usually Sinopec or the China National Petroleum Corporation (CNPC). The NOC is required to deposit the payment in the borrower's account with the Export-Import Bank of China, which is then used to service the loan. An important condition of the loans is that the infrastructure projects should be built by Chinese contractors. As the projects are not allocated to contractors through open auctions, it could cause efficiency loss. The advantage of the resource-backed loans is that these loans are not given out in cash and the money always stays in China. Hence, it can safeguard against the corruption problem that is often associated with infrastructure projects. In addition, it can also avoid currency inconvertibility, political instability and expropriation.

3.2.4. Internal Finance

Although both involve the government and private firms, the difference between internal finance and PPP is that internal finance provides all the funding for the infrastructure projects while under PPP private firms may be responsible for the cost of investment. In terms of cost-effectiveness, internal-financed projects are generally untied and are also subject to corruption.

3.3. Cost-Effectiveness Comparison of Financing Methods

This subsection is devoted to the qualitative comparison of the current major financing methods, including ODA, PPP, resource-backed loans and internal finance, in terms of their cost-effectiveness. We will focus on two important factors of cost-effectiveness, namely the tiedness of the fund and the corruption that is potentially involved. Tied aid is foreign aid that must be spent on hiring firms of the country providing the aid (the donor country) or on firms from a group of selected countries. This will prevent procurement from occurring through international competitive bidding and hence cannot ensure best value for money. Evidence has shown that tying of aid can increase the cost of a development project as much as 15-30% (Clay, Geddes and Natali, 2009). In addition to tiedness, corruption is also a major concern. The infrastructure sector has been regarded as the sector that is most prone to corruption due to the idiosyncratic capital designed for installation and the network feature of the associated government regulation (Collier and Hoeffler, 2005). For example, Caselli and Michaels (2013) have shown that rent sharing and embezzlement by government officials have prevented Brazil's resource revenues from being translated into infrastructure. Table 5 gives a summary of the comparison between the financing methods in terms of the two factors.

For internal finance, it is not tied, but is subject to corruption. ODA is in general partially tied, with an increasing trend for the proportion of untied aid. And ODAs may involve corruption as money is directly handed to African governments. PPPs are generally untied. But as they are contracts between the government and private firms, they may involve corruption. Resource-backed loans from China are tied. However, corruption can be eliminated because loans are not given out in cash and the money always stays in China. This is because loans are mainly provided by Export-Import Bank of China, with repayments guaranteed by the sale of a certain amount of natural resources throughout the loan repayment period to a specified Chinese National Oil Company. The National Oil Company is required to deposit the payment in the borrower's account with the Export-Import Bank of China, which is then used to service the loan.

Table 5: Cost-Effectiveness Comparison

	Tiedness	Corruption
Internal Finance	No	Yes
ODA	Partially tied to the donor country	Yes
PPP	No	Yes
Resource-backed Loans	Tied to Chinese contractors	No

Therefore, from Table 5, we can see that all the financing methods have their own advantage and disadvantage and it is hard to rank their effectiveness based on the qualitative analysis. Quantitatively, although it is generally difficult to measure the above advantage and disadvantage separately, it is possible to evaluate their overall effects in terms of their effectiveness of transforming investments into welfare.

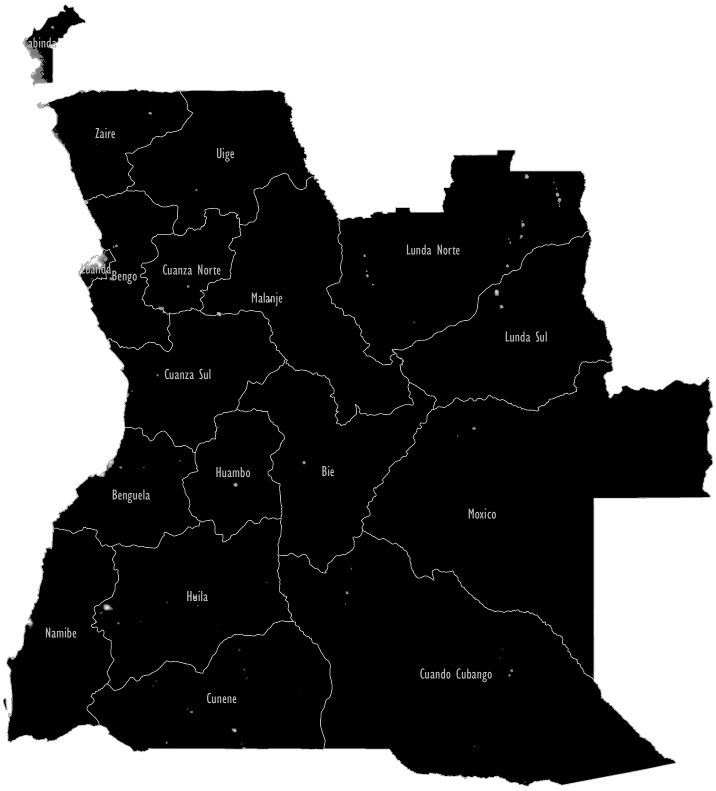
4. Data

To examine the relationship between power sector investments and lights, we assembled detailed information on the Angola power sector including details on specific investment projects across time and location, by investment value, infrastructure type and source of finance.

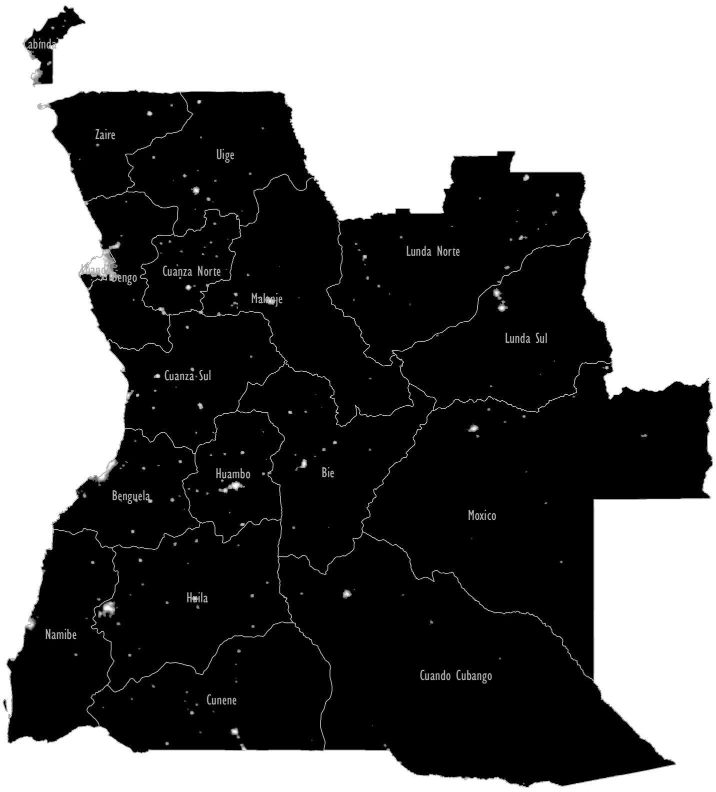
4.1. Nighttime Lights

To measure changes in power consumption as a result of a power infrastructure project, we use the increases in luminosity in DMSP/OLS in the areas that can be affected by the project through power transmission lines. For the non-calibrated DMSP/OLS data, the relationship between power consumption and luminosity is usually log-linear. As Angola does not have a complete national grid, and it currently has three independent systems that provide power to different parts of the country, we seek to identify the impact of each power infrastructure project on specific regions of the country. In addition, the data on nighttime lights also has one advantage over the data collected through ground-based surveys regarding the measurement of power consumption. This is because the ground-based data collection is difficult and hence rarely available, especially in the rural areas. However, there have been some studies, Min et al. (2013) for instance, using the data from the ground-based surveys to show the significant correlation between lights observed at night and access to electricity in rural areas. Therefore, the use of nighttime light data is more cost-effective compared with other ground-based data collection.

Since the civil war ended in 2002, a large amount of power infrastructure investments have lit up the sky of Angola (Figure 3). The next subsection describes the power infrastructure investments behind the increase in lights.



(a) 2002



(b) 2013

Figure 3: Angola’s nighttime lights in 2002 and 2013

4.2. *Power Infrastructure Investments in Angola*

4.2.1. *The Electricity Sector of Angola*

The existing infrastructure in Angola's electricity sector was built well before independence, which occurred in 1975. Much was damaged during the Civil War, which ended in 2002. As a result, only a small percentage (40.2% in 2010) of the population has access to electricity.

The state-owned public utility to transmit and distribute electricity in Angola is Empresa Nacional de Electricidade (ENE), which is responsible for supplying the main urban centres, with the exception of the capital Luanda. Distribution to Luanda is the responsibility of EDEL (Empresa de Electricidade de Luanda). The country's installed capacity is on three non-interconnected networks and several smaller isolated grids. The north, south, and central systems each have their own networks linking generation sources to load centers. The northern system, serving Luanda, accounts for over 80 percent of the country's generation assets, while the central and southern systems have less than 10 percent each. Only about 70% is operational. Hydro accounts for a little over 60% of installed capacity, while the rest is primarily diesel-fired thermal.

4.2.2. *Oil-Backed Loans in Angola*

The low electrification rate in Angola is mainly due to chronic under-investment in infrastructure. Traditionally, domestic public finance, ODA from OECD countries and PPP have been crucial in financing infrastructure projects. Now China's resource-backed loans have become another major source of finance. And Angola has become the biggest receiver of resource-backed loans from China.

According to the Angolan Minister of Finance, by late 2011 three credit facilities totalling US$ 7.5 billion for infrastructure construction had been contracted with the Export-Import Bank of China (US$ 2 billion in 2004, US$ 2.5 billion in 2007 and US$ 3 billion in 2011). All loans are secured by oil (Alves, 2013). The electricity sector has been the main focus of these loans.

The loan started from 2004 is payable over 12 years at a deeply concessional interest rate, Libor plus a spread of 1.5 percent, with a grace period of up to three years. It is divided into two phases, with $1 billon assigned to each. The first phase of this credit line involved 31 contracts on energy, water, health, education, communication, and public works. This corresponds to 50 projects across the whole country, valued at $1.1 billion. The second phase of this loan will fund implementation of 17 contracts, involving over 52 projects, some of which are unfinished projects of the first phase. For the loan started from 2007, the repayment terms were increased to 15 years with a revised interest rate of Libor plus 1.25 percent. Conditions attached to Chinese exports were relaxed, but the local-content rules for reconstruction were tightened to ensure greater local participation (Campos and Vines, 2008). Regarding the power infrastructure financed by China, there are more than 20 projects since 2004, which include rehabilitation and construction of power plants, transmission line and substations etc. The costs of projects range from US$ 15 million to more than US$ 200 million.

4.2.3. Data on Power Infrastructure Investments in Angola

For the data on power infrastructure investment in Angola, we use World Bank-PPIAF database, aiddata.org, Query Wizard for International Development Statistics (QWIDS), Angola's Ministry of Finance and various web sources to obtain the costs, time frame, locations and other characteristics of the infrastructure projects.

Table 6 and 7 list the summary statistics regarding the distribution of investment costs and the number of projects by financing methods and infrastructure types. We can see that in terms of financing methods, the biggest source is internal finance. The second is resource backed loans, which is followed by PPP and ODA. However these investments are not uniformly distributed across all infrastructure types. Internal finance and PPP put more weights on generation. While ODA and resource backed loans focus on distribution. In terms of the number of projects, we can see that internal finance has been used for much more projects than the other three methods. Combining Table 6 and Table 7, we can calculate the average project cost in Table 4. We can see that internal finance, ODA and PPP generally finance small projects, while resource backed loans generally finance much larger projects.

Table 6: Distribution of Investment Costs in Angola's Power Sector from 1996 to 2012 (constant 2005 US$, million)

	IF	ODA	PPP	RBL	Total
Distribution	691	73		274	1038
Generation	1242	4	26	74	1346
Illumination	117				117
Transmission	719	18		126	862
Total	2770	94	26	473	3363

Table 7: Distribution of Investment Projects in Angola's Power Sector from 1996 to 2012

	IF	ODA	PPP	RBL	Total
Distribution	190	14		9	213
Generation	209	5	5	2	221
Illumination	161				161
Transmission	26	3		5	34
Total	586	22	5	16	629

Table 8: Average Project Cost in Angola's Power Sector from 1996 to 2012 (constant 2005 US$ million)

IF	ODA	PPP	RBL	Total
4.7	4.3	5.2	29.6	5.3

In terms of the geographic distribution of the projects, from Figure 4, we can see that most ODA and PPP projects are located around a few big cities, such as Luanda. For other methods, there are no geographic clustering.

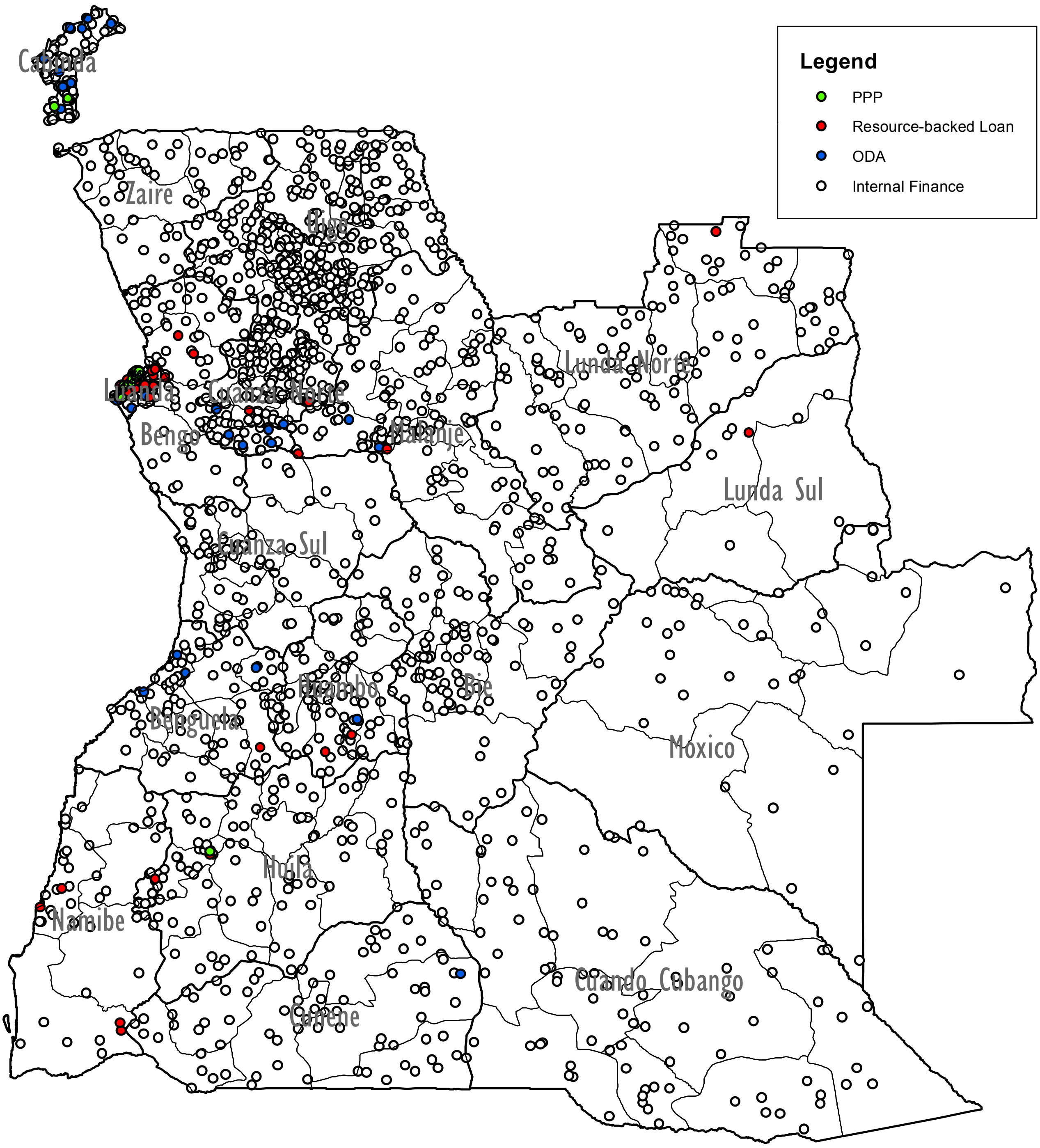


Figure 4: Distribution of power projects in Angola

4.2.4. *GDP Growth, Nighttime Lights and Power Infrastructure Investment*

In the literature, a stable relationship is usually assumed between GDP and nighttime lights. But in a country like Angola, where there is a large funding gap for power infrastructure and power consumption is mainly determined by the supply of infrastructure, infrastructure investments should be a more relevant determinant of nighttime lights instead of GDP. This is evident in the figures below, which show that in the case of Angola there is no significant statistical relationship between GDP growth rate and lights growth but increase in lights strongly co-move with infrastructure investment. These observations are also confirmed by the estimation in Table 9.

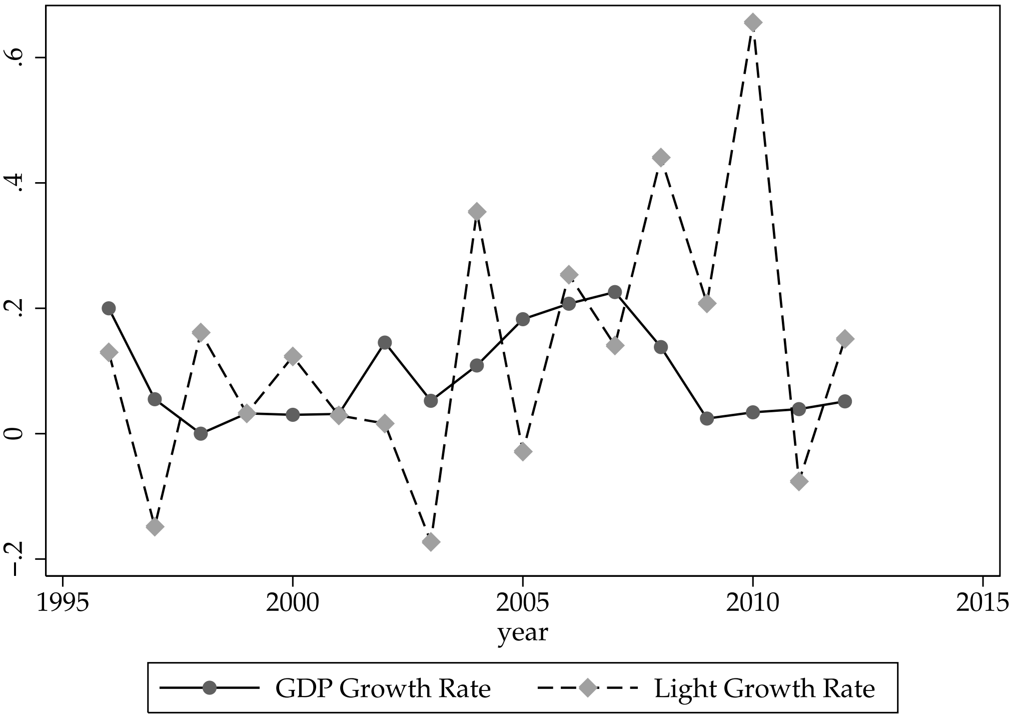


Figure 5: GDP Growth Rate and Lights Growth Rate in Angola

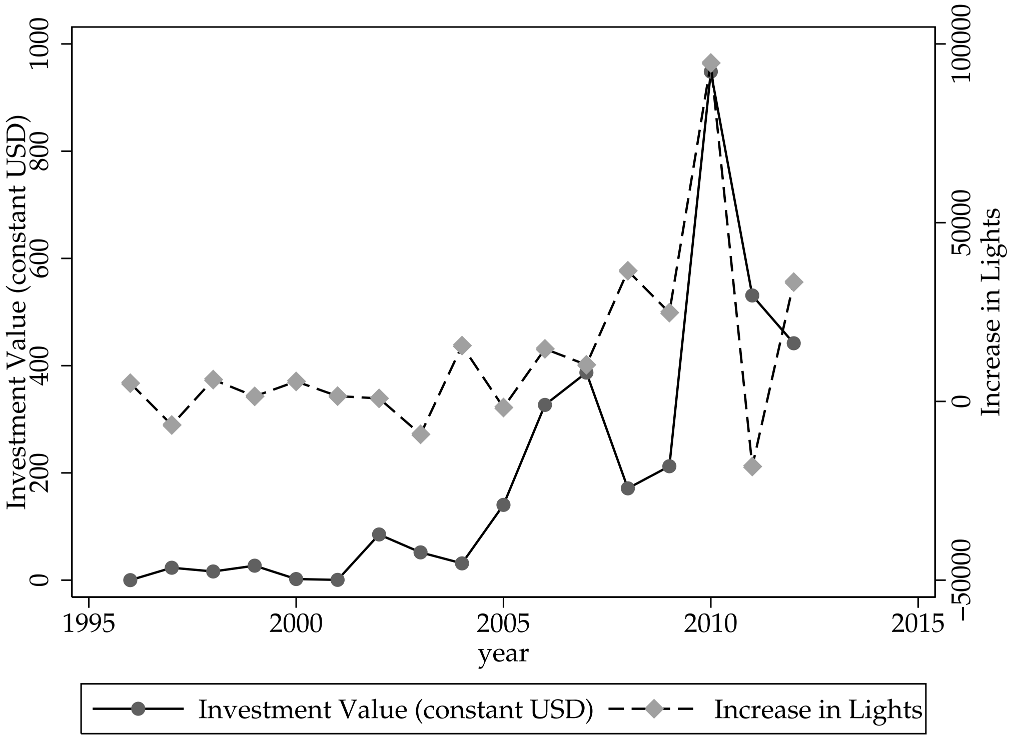


Figure 6: Power Infrastructure Investment and Increase in Lights in Angola

Table 9: GDP, Lights and Power Infrastructure Investment in Angola 1996-2012

	(1)	(2)
Independent Variable	Light Growth Rate	Increase in Lights
GDP Growth Rate	0.324	
	(0.443)	
Investment		66.42***
		(17.95)
Constant	0.0877	-320.6
	(0.0546)	(5,564)
Observations	21	18
R-squared	0.027	0.461

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Therefore, the evidence suggests that lights in these bad data countries are more determined by the supply side as measured by investments than by the demand side as measured by GDP. Moreover, given the low effectiveness of converting power infrastructure investment to electricity in Angola shown later, if we assume all countries in Table 1 spend the same fraction of GDP on power infrastructure investment, then simply using growth of night lights as a proxy for GDP growth will underestimate the true GDP growth for Angola. This is consistent with Table 6 and Figure 7 in Henderson, Storeygard and Weil (2012), which show that Angola rank second in terms of underestimating GDP growth using lights data. Average annual GDP growth rates over the period of 1992/93-2005/06 are 6.99% in Angola according to WDI, while predicted growth rates simply based on lights data are only 3.88%.

5. Empirical Strategies

We seek to estimate specific elasticities for the responsiveness of lights to different types of investment by infrastructure type and by financing method.

5.1. Assumptions

Angola has 18 provinces. Within each province, there are several municipalities. In total, there are 163 municipalities. The municipality is our unit of analysis. And the general strategy is to match projects with municipalities and link the investment of the projects with the change in luminosity in the affected municipalities to calculate the cost-effectiveness of transforming investment to welfare. We can do this matching in Angola because the electric system in Angola is segmented and Angola's installed capacity is on three non-interconnected networks. Figure 7 shows Angola's electric system in 2015 and its projected evolution in the future, where the solid lines represent the existing system. We can see that most places are connected to one power plant through one transmission line. Therefore, for a distribution project in a particular municipality, we can match the project with it. For a transmission project, we can match the project with the end points of the transmission line. For a generation project, we can match the project with the municipalities that can be affected by the project through transmission lines.

To carry out the empirical strategy, we make the following three assumptions. First, we ascribe the luminosity increase in the year after the project was built to the project investment. We use the year right after the project was built because later on the link between the project and the luminosity increase will be weakened, but the initial jump can be associated with the new infrastructure.

The second assumption is that this is a measurement exercise rather than an identification exercise. This is because in Angola, also as in many other African countries, power infrastructure projects are planned every five years. What the government does is that they first use economic forecasts of regional economic growth to forecast the future demand of electricity. Next, a least cost expansion model is used to minimize the cost of investment to meet the forecasted electricity demand. Therefore using the model, the government can decide what generation plants, transmission lines and substations to be built in the next few years and their estimated costs. In this sense, the power consumption increase is pre-determined. It's not the endogenous variable. So in the paper we just use luminosity data to measure it. We cannot use the government's model to calculate the expected electricity demand at the municipality level as all the economic indicators are only available at the province level.

The third assumption is that power consumption in Angola is mainly constrained by the supply side. This assumption is reasonable as the Ministry of Finance sets electricity tariffs that are uniformly low throughout the country. These are currently at levels that do not cover costs. As a result, power consumption as measured by night-time lights is a good measure of welfare. From Figure 5 we can see that GDP growth significantly slowed down since 2009. In order to satisfy our assumption that power consumption is mainly constrained by the supply side but not by the demand side, we use the sample from 1996 to 2009 for our estimation.

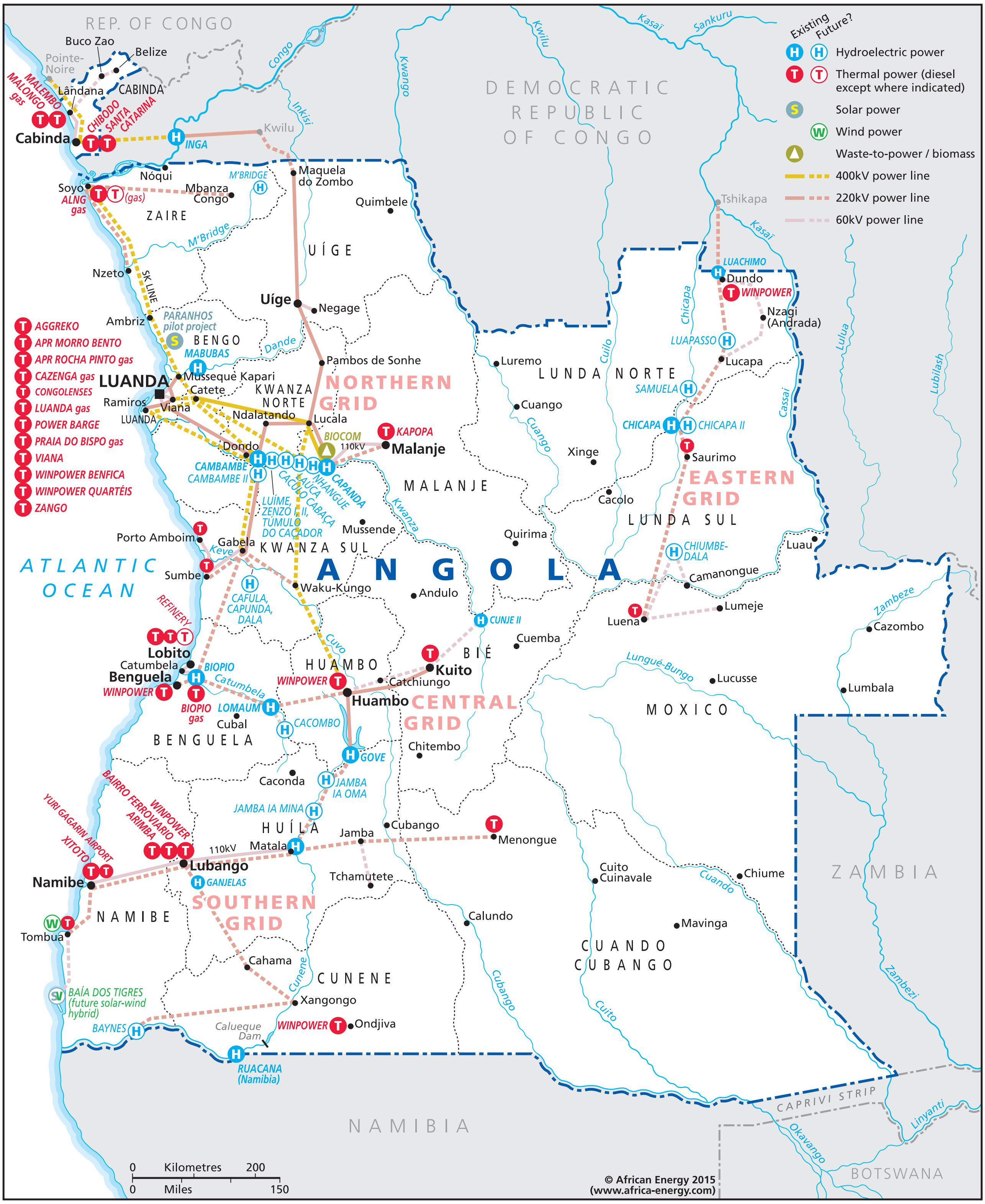


Figure 7: Angola Electric System in 2015

5.2. *Outcome Equation*

Under these assumptions, we link the data on luminosity and the data on investment, and set up our empirical model. Let y_{it} be the total power consumption in area i at time t. In this paper, we use the sum of luminosity of nighttime lights recorded by the Defense Meteorological Satellite Program (DMSP) over area i as a proxy for the power consumption. x_{itc} is the stock of investment financed by method c in area i at time t. Then the general relationship between y_{it} and x_{itc} can be characterized by

$$y_{it} = \alpha_0 + \alpha_1 t + \sum_{c \in \Omega_c} \beta_c x_{itc} + \mu_i + \delta_t t + \epsilon_{it},\ \Omega_c = \{ODA, RBL, PPP, IF\}$$

where c is the index of financing methods. β_c is the measure of the effectiveness of transforming investment to electricity use for financing method c. μ_i is the fixed effects for area i. $\alpha_1 t$ is the common time trend. $\delta_t t$ is the time-varying trend, and we assume the trend is time-varying because the time trend of electricity use can be affected by the time-varying factors from the demand side or supply side of electricity use, such as aggregate economic growth. ϵ_{it} is the error term.

We can compute the first difference of the above equation and obtain

$$\Delta y_{it} = \alpha_1 + \sum_{c \in \Omega} \beta_c \Delta x_{itc} + \delta_t + \Delta\epsilon_{it} \tag{1}$$

This equation can be used to compute the cost-effectiveness for different financing methods, i.e. β_c.

5.3. *Selection Model*

However, the choice of financing methods for a project may not be exogenous. The choice is jointly determined by the government and financiers. Without taking into account the endogeneity of choice, estimating the effectiveness of investments using the above equations may generate biased results due to the selection of financing methods. For example, the financier of a financing method may have a strong preference to fund the projects close to natural resources in order to take advantage of the resource boom. In this case, without correcting the selection bias, the effectiveness of this financing method will be upward biased. We illustrate the problem in details as follows:

Given the above outcome equation, when the only project completed in area i at time t is an ODA project, we have

$$\Delta y_{it}^{ODA} = \alpha_1 + \beta_{ODA} \Delta x_{it,ODA} + \delta_t + \Delta\epsilon_{it}$$

where Δy_{it}^{ODA} denotes the power consumption increase when ODA is used for the project in area i. However, there is also an implicit selection model governing the choice of financing methods:

$$V_{it}^{c} = z_{it}\gamma_c + \eta_{it}$$

where V_{it}^{c} is the utility for the selector of financing methods when method c is used for the project in area i. z_{it} is the set of explanatory variables of the utility. γ_c is the coefficient for method c and η_{it} is the error term. Without loss of generality, the outcome variable Δy_{it}^{ODA} is observed if and only if ODA is chosen, which happens when

$$V_{it}^{ODA} > max_{c \neq ODA}(V_{it}^{c})$$

Therefore, the error term in the outcome equation $\Delta\epsilon_{it}$ may not be purely random and may depend on the explanatory variables in the selection equation z_{it}. As a result, any correlation between z_{it} and Δx_{it} will bias our estimate of β_{ODA}. To solve the problem, we follow the literature to model the selection problem as a multinomial logit model and estimate it jointly with the outcome equation (Bourguignon, Fournier and Gurgand, 2007). In terms of the explanatory variables in the selection equation, in this paper we use project size, distance to natural resources, % of landmine-impacted communities, and infrastructure type. As shown in Section 4, due to the infrastructure funding gap in Angola and the recent large supply of loans from China in the form of resource-backed loans, large projects are usually allocated to RBL. In addition, projects of different types are not randomly allocated to financing methods, as shown in Table 6 and Table 7. We also include % of landmine impacted communities in z_{it} as Angola has long been recognized as one of the most landmine contaminated countries in the world. It is said that about 6 million landmines have been planted during the Civil War. According to Landmines Impact Survey completed in 2007, there are 2.4 million people (17% of all citizens) live in the landmine-impacted communities. There were recently 341 victims of landmine accidents, 163 of which were killed. Therefore, we have a good reason to believe that contractors, especially those from overseas, have a strong incentive to work in the area less affected by landmines. Given the substantial variation in the distribution of landmines as shown in Figure 8 and Table 10, danger of landmines for each project can be a good explanatory variable in the selection equation. From the summary statistics in Table 11, we can see that projects financed by RBL are least affected by landmines, which is followed by ODA and PPP, while projects financed internally are less risk averse to landmines. Finally, as Angola is a resource-rich country, distance to resources should also be a good predictor of the financing method, as some financiers may want their projects close to natural resources in order to take advantage of the future economic development of the area. Figure 9 shows the distribution of natural resources in Angola, including onshore and offshore oil, diamond and other minerals. From Table 11, it seems that on average ODA and PPP are more likely to finance projects close to natural resources than IF and RBL.

Figure 8: Landmines in Angola

Table 10: Prevalence of Communities Affected by Province in the Landmine Impact Survey

Province	Total Communities	Impacted Communities	% of Impacted Communities
Moxico	1,698	290	17
Bie	2,825	282	10
Uige	2,208	172	8
Kuando Kubango	886	171	19
Kwanza Sul	1,997	169	8
Huambo	2,938	153	5
Benguela	1,807	127	7
Kunene	426	126	30
Malanje	1,868	87	5
Bengo	543	74	14
Lunda Sul	736	73	10
Hula	1,863	72	4
Zaire	741	66	9
Kwanza Norte	815	64	8
Lunda Norte	1,059	30	3
Cabinda	387	27	7
Namibe	420	3	1
Luanda	291	2	1
Total	23,508	1,988	8

Table 11: Danger of Landmines and Distance to Resources by Financing Methods

	IF	ODA	PPP	RBL	Total
Impacted Communities (%)	8.0	5.1	4.0	3.4	7.8
Distance to Resources (decimal degrees)	0.59	0.31	0.27	0.46	0.57

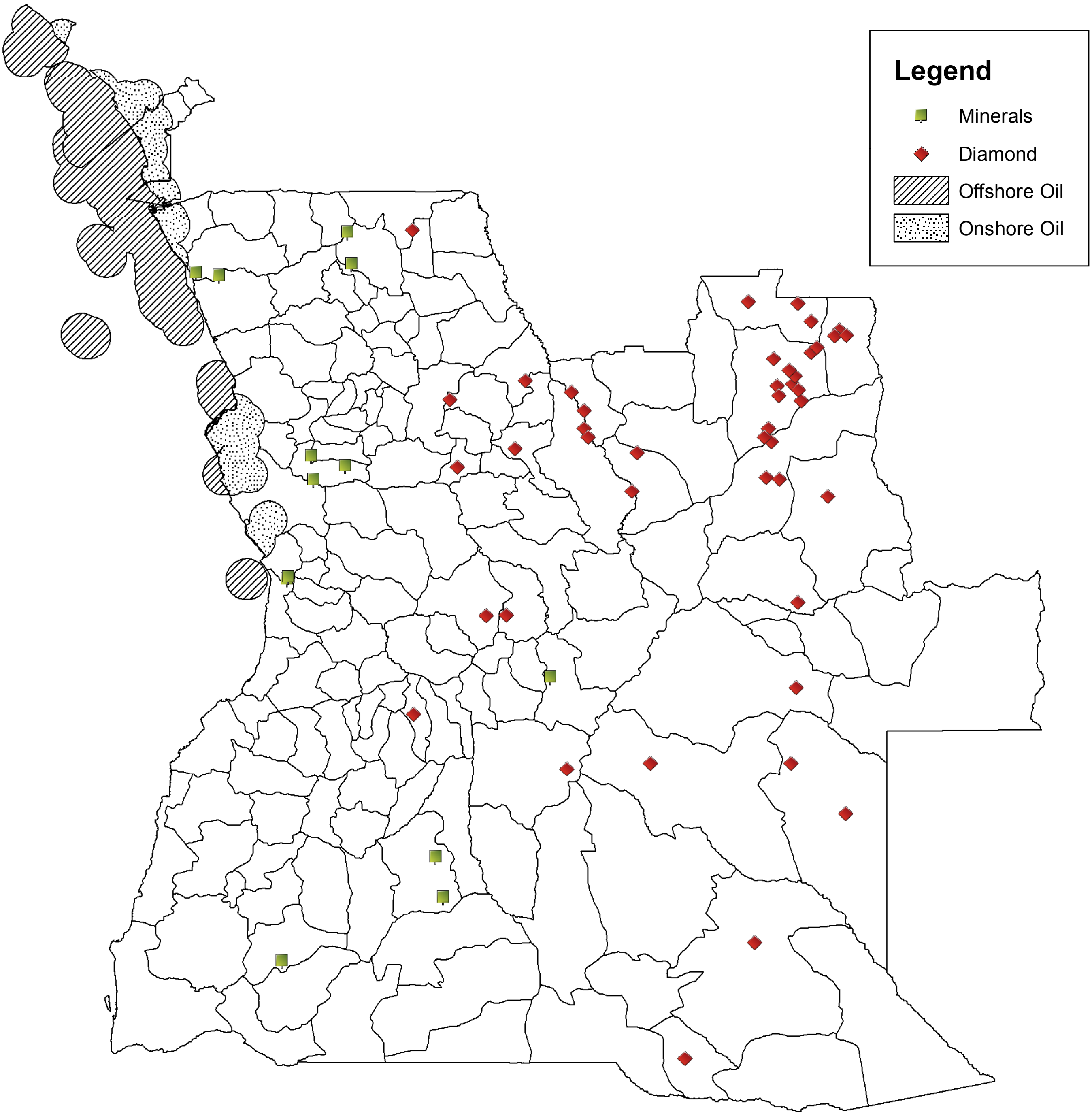


Figure 9: Angola Resource Map

6. Empirical Results

The estimation results for the outcome equation without taking into account the selection equation are summarized in Table 12. In column (1), the overall effectiveness of investment is estimated. The point estimate shows that every 1 million real US dollar investment can increase the lights by 39.09 units. In column (2) controlling for the year fixed effects does not change the overall effectiveness very much. In column (3), we distinguish between different financing methods and estimate the effectiveness of investment separately. The results show that the effectiveness of RBL, ODA, PPP and IF are significantly positive. In terms of the order of effectiveness, PPP is the most effective method, which is followed by RBL. And ODA and IF rank third and fourth respectively. In column (4), controlling for the year fixed effects does not change the order of effectiveness. In Table 13, we also estimate the effectiveness of investment by infrastructure type. We can see that with or without the year fixed effects, investment in distribution is the most effective way of increasing lights. This is followed by investment in transmission and illumination. However, the effectiveness of investment in generation is not significant. One possible explanation could be that some investments in generation projects are not actually implemented.

When we correct the selection bias and estimate the outcome equation and selection equation simultaneously, the order of effectiveness by financing methods changes. Table 14 shows the estimation results for the selection model. First, the estimated coefficient of % of impacted communities are significantly negative for ODA and RBL, which implies that these two methods are more risk-averse to landmines compared with other methods. Second, ODA tends to finance the projects close to natural resources but this is not the case for other methods. Third, ODA and RBL are more likely to finance distribution and transmission projects. Finally, the coefficient of project size is significantly positive for RBL, implying that larger projects are more likely to be financed by RBL. After controlling all these selection bias, the estimates of effectiveness by financing methods are shown in Table 15. We can see that after the correction of selection bias, RBL becomes the most effective method, which is followed by IF. And ODA and PPP are less effective than the other two methods. We also combine the empirical results from Table 12 and Table 15 to perform a Hausman specification test in order to see whether the selection bias is significant. The Hausman test is rejected at 1% level, which means that the selection bias is significant and it is necessary to jointly estimate the outcome equation with the selection equation in order to correct the selection bias.

Table 12: Estimation of the Outcome Equation

	(1)	(2)	(3)	(4)
	Δy_{it}	Δy_{it}	Δy_{it}	Δy_{it}
Δx_{it}	39.09***	38.26***		
	(1.156)	(1.142)		
$\Delta x_{it,RBL}$			93.72***	93.60***
			(2.860)	(2.806)
$\Delta x_{it,ODA}$			37.43***	37.29***
			(9.819)	(9.590)
$\Delta x_{it,PPP}$			185.5***	157.9***
			(30.37)	(29.97)
$\Delta x_{it,IF}$			11.06***	10.41***
			(1.584)	(1.555)
Constant	30.48***	-41.74	37.04***	-41.74
	(9.457)	(30.24)	(8.271)	(26.25)
Year fixed effects		Yes		Yes
Observations	1700	1700	1700	1700
R^2	0.403	0.432	0.546	0.573

Standard errors in parentheses

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

Table 13: Estimation of Investment Effectiveness by Infrastructure Type

	(1)	(2)
	Δy_{it}	Δy_{it}
$\Delta x_{it,distribution}$	68.78***	66.24***
	(3.617)	(3.561)
$\Delta x_{it,transmission}$	48.96***	49.45***
	(2.596)	(2.540)
$\Delta x_{it,generation}$	-0.4894	-0.5470
	(1.903)	(2.831)
$\Delta x_{it,illumination}$	41.47***	32.82***
	(9.278)	(9.173)
Constant	29.83***	-41.72
	(8.139)	(25.91)
Year fixed effects		Yes
Observations	1700	1700
R^2	0.560	0.584

Standard errors in parentheses

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

Table 14: Estimation of the Selection Equation

	Coefficient	Standard Error
ODA		
Impacted Communities (%)	-8.92*	5.30
Distance to Resources	-.85	.55
$D_{distribution}$	1.92***	.54
$D_{transmission}$	2.46***	.81
Δx_{it}	-.03	.03
Constant	-3.38***	.51
PPI		
Impacted Communities (%)	-12.81	14.13
Distance to Resources	-.77	1.24
$D_{distribution}$	-13.99	739.18
$D_{transmission}$	-14.67	2065.83
Δx_{it}	.02	.01
Constant	-3.41***	.69
RBL		
Impacted Communities (%)	-29.14***	10.21
Distance to Resources	.21	.44
$D_{distribution}$	2.33***	.79
$D_{transmission}$	3.13***	.94
Δx_{it}	.02**	.01
Constant	-4.15***	.79

Table 15: Estimation of the Outcome Equation with Selection Bias Corrected

	(1) Δy_{it}	(2) Δy_{it}
$\Delta x_{it,RBL}$	95.33***	96.36***
	(7.72)	(7.60)
$\Delta x_{it,ODA}$	-1.828	-3.316
	(11.56)	(11.32)
$\Delta x_{it,PPP}$	-49.86	-56.17
	(35.91)	(35.28)
$\Delta x_{it,IF}$	3.485**	3.438**
	(1.650)	(1.623)
Constant	24.15***	-44.90
	(7.94)	(25.10)
Year fixed effects		Yes
Observations	1700	1700
R^2	0.589	0.610

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7. Conclusion

This paper sets up the general framework of estimating the cost-effectiveness of power infrastructure investments by financing method and by infrastructure type. It also estimates the overall impact of infrastructure investment on nighttime light increase, which should be a more relevant relationship compared with the relationship between GDP and nighttime lights, in a country like Angola, where there is a large funding gap for power infrastructure and power consumption is mainly driven by the supply of infrastructure. In addition to the broken link between GDP and lights, as shown above, at the national level, their links are also expected to be broken at subnational and supranational levels.

Therefore, the evidence in this paper points out a paradox in using satellite data on night lights as a proxy for economic activities, such as GDP or GDP growth: the countries for which the method is needed the most, i.e. the countries with poor statistical capacity, are just the countries, for which the assumption of the method is satisfied the least, i.e. the countries with a large power infrastructure deficit. Therefore, the application of this method in countries with poor power infrastructure should be implemented with cautions and should take in account the changes in power infrastructure when interpreting their results.

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