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Leonardo R. Corral
Maja Schling
César Montiel

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The Economic and Ecological Impact of Natural Resource Extraction:
The Case of the Camisea Gas Project in Peru

Leonardo R. Corral[1]
Maja Schling[2]
César Montiel[3]

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Abstract

This paper presents the first rigorous empirical evidence of the impact of a large hydrocarbon project in both its economic and environmental dimension. Concentrating on Peru's largest hydrocarbon project, the Camisea Gas Project, which began operating in the dense Amazonian jungle under strict environmental safeguards in 2004, we assess whether natural resource extraction can have beneficial economic effects without causing negative environmental externalities. The analysis relies on the synthetic control method to systematically choose comparison units (departments), which allows for precise quantitative inference in small-sample studies. Our results indicate that in six of the eight years since the Camisea gas fields began operating, local economic effects, as measured by nighttime lights data, are robustly positive. An examination of remotely-sensed vegetation data suggests that the Camisea Gas Project did not have a significant effect on deforestation, suggesting that the implementation of stringent safeguards can help mitigate environmental risks.

JEL Codes: O44; Q32; D04; N56

Keywords: Natural Resources; Economic Growth; Nighttime Lights Data; Deforestation; Synthetic Control; Environmental Safeguards

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[1] leonardoc@iadb.org; Inter-American Development Bank
[2] majas@iadb.org; Inter-American Development Bank
[3] cesarmo@iadb.org; Inter-American Development Bank

1 Introduction

Whilst the exploitation of a country's oil and gas reserves promises economic growth, these hopes can go unfulfilled. The capture of windfall rents by local politicians, the undermining of local institutions, and low local absorptive capacity are some of the issues recently addressed in the literature (Vicente, 2010; Caselli & Michaels, 2013; Gadenne, 2017; Loayza et. al., 2014; Corral et. al., 2016). More broadly, these issues have been attributed to a "natural resource curse" (Robinson et al., 2006; Dalgaard & Olson, 2008; Van der Ploeg, 2011). The exploitation of oil and gas reserves can also be controversial and face scrutiny by environmental organizations, particularly when reserves are found in areas of renowned cultural and biodiverse richness (The Economist, 2003). Further, realized economic and environmental outcomes might be dependent on the political-economic interactions between key parties involved, i.e. governments, extraction firms, environmental organizations, and lenders (Schopf & Voss, 2018).

In this article, we analyze the economic and ecological impacts of Peru's biggest energy project, the Camisea gas project, on the Department of Cusco, where the natural gas is found[4]. As the producing region, Cusco benefits from royalty transfers. To this end, we address the non-random siting of the project, so as not to conflate the environmental and economic effects of the project with the effects of pre-existing conditions. We rely on the synthetic control method to systematically choose comparison units (other departments), which allows for precise quantitative inference in small-sample studies (Abadie & Gardeazabal, 2003). To circumvent data limitations, we use remotely-sensed satellite imagery on lights at night as a proxy for economic growth (Henderson et al., 2012) and the Normalized Difference Vegetation Index (NDVI) for forest cover (for a recent application see BenYishay et. al., 2017). The policy relevant question is whether and under what conditions can extractive industries lead to economic growth without spurring deforestation, both directly and indirectly through royalty transfers.

The economic impacts of natural resource endowments have received widespread attention in the literature. Though some studies highlight the positive effects of natural resource endowment (i.e. oil, gas, fisheries, mining, forestry), finding that backward linkages to local input markets and strengthened local institutions may benefit economic development (Collier & Hoeffler, 2004; Aragón & Rud, 2013; Lippert, 2014), other studies note the perils of a "resource curse", which associates resource wealth with a number of economic and political woes

[4] Peru's territory consists of departments (or regions), provinces, and districts. Specifically, the country is divided into 26 units: 25 departments and the province of Lima. Departments are subdivided into provinces, and all provinces are subdivided into districts. In each jurisdiction, national, departmental, and local governments were constituted and organized

(Robinson et al., 2006; Dalgaard & Olson, 2008; Van der Ploeg, 2011). What has received significantly less attention, however, are the environmental consequences of the large infrastructure projects that the exploitation of the natural resource usually encompasses. Research shows that infrastructure extension is among the leading global causes of deforestation (Barbier & Burgess, 1996; Geist & Lambin, 2002; Mayaux, 2013). Given that carbon emissions caused by forest clearing contribute approximately 20% to the global total of greenhouse gases, the long-term consequences of climate change, in addition to the significant loss of biodiversity, are of major concern (IPCC, 2007).

A well-rounded approach to assessing the sustainability of large hydrocarbon and other infrastructure projects should therefore consider both its economic and environmental impacts. Such evidence is mostly absent from the literature, with two noteworthy recent exceptions. For the Democratic Republic of Congo, Damania et al. (2017) examine the tradeoff of economic benefits and adverse environmental impacts that come with the expansion of the road network. Although improved road connectivity boosts economic growth and trade due to decreased transportation costs, road construction also results in increased deforestation and significant biodiversity loss. The authors find that forest clearing intensity increases considerably by 3.1% with each 10% decrease in distance from a road. Considering both the economic and environmental effects of a conditional cash transfer program, Alix-Garcia et al. (2013) examine the impact of the *Oportunidades* program in Mexico and find that, although the program has poverty-alleviating effects on beneficiary households, it comes at the cost of environmental degradation: Exposure to the program doubles the probability of deforestation occurring near a beneficiary community, and deforestation rates increase by 15 to 33% in communities that had previously cleared forests. These observations appear to be in line with previously proposed theoretical frameworks for analyzing deforestation dynamics along a country's economic development path: According to the von Thünen model, land use is a function of rent maximization, so that land use is determined, among other factors, by location. Hence, easier access to forested land, facilitated by road networks, increases payoffs to alternative activities, such as agriculture, thereby encouraging deforestation (Angelsen, 2007).

To account for these potentially adverse environmental effects, environmental organizations, development agencies and donors have demanded more stringent environmental and social safeguards from project developers. In this context, environmental and social impact studies (EIA) that draw on various disciplines including biology, ecology, and environmental science can help identify areas of high ecological value and then select appropriate measures such as enhancing property rights, creating end enforcing protected areas, and wildlife sanctuaries, to protect the most vulnerable areas (Wunder & Sunderlin, 2004; Wright et al., 2013). These environmental safeguards are often complemented by social safeguards to protect the livelihoods and ethnic diversity of local communities affected by infrastructure projects. Particularly in the tropics, where many indigenous communities still rely on forest resources as their principal source of income, social safeguards are a useful tool to address concerns over the expropriation of and encroachment on communal forest areas (BenYishay et al., 2016). In this context, research has found that land rights formalization is generally associated with slower deforestation and better agricultural results (Robinson et al., 2014; Lawry et al., 2017). However, the extent to which governments and extraction firms can be lobbied to incorporate stringent environmental and social safeguards depends on the relative bargaining power of the parties involved (Schopf & Voss, 2018).

In this paper we study the effects of the Camisea Gas Project, Peru's biggest energy project, on the economic development and forest cover change of the department of Cusco, where the resource is found. Camisea has proven reserves of 9 trillion cubic feet of natural gas. In 2000, Peru's government awarded licenses to develop the Camisea field and to build and operate a 700 km (440 mile) pipeline to the Peruvian coast (Inter-American Development Bank, 2002). The Camisea fields are deep in one of the more pristine parts of the Peruvian jungle. Its opponents at the time claimed that the project threatened isolated tribes of Amazon Indians, rare species and the rainforest (The Economist, 2003). This led the Inter-American Development Bank (IDB), who provided $75m loan for the pipeline construction, to carry out detailed environmental and social-impact studies and propose a series of design modifications and actions to mitigate the potential negative impacts. As a result, the extraction firm used "offshore" technology at Camisea: drilling sites were operated as if they were islands in the jungle (IDB., 2003). Workers and supplies were helicoptered in, and no access roads were built. These efforts were meant to minimize risks of colonization from the highlands and illegal extraction activities in the pristine rainforest. In parallel, the IDB also provided a $5 million "institution-building" loan to the Government to help it police the Camisea project and support sustainable development planning in affected areas. This led to the creation of four new protected areas[5] covering close to a million hectares (12.8% of the total territory of the Department of Cusco), the titling of 28 native communities[6] and the issuance of over 10,000 property titles (IDB, 2007). Since the gas project's operational inception in 2004, the

[5] Recent evidence for Peru finds that protected areas are effective in reducing deforestation rates (Miranda et. al. 2016).
[6] Evidence for Peru finds that titling native communities in the jungle area stems deforestation (Blackman et.al., 2017). See also Blackman and Veit (2018).

Department of Cusco has enjoyed significant windfalls and receives approximately $300 million annually in transfers from the central government earmarked for capital investments, including roads.[7]

In order to estimate the impact of the Camisea Gas Project on Cusco's economic and environmental outcomes, we need to identify the counterfactual path of economic and environmental outcomes that would have existed in the absence of Camisea. A comparison group consisting of departments sharing common pre-Camisea economic and environmental trends can be constructed for this purpose. To do this we employ a data-driven combination of control units, namely the synthetic control method of Abadie and Gardeazabal (2003), extended in Abadie et al. (2010), which Athey and Imbens (2017) have touted as "arguably the most important innovation in the policy evaluation literature in the last 15 years."

In the natural resource extraction literature, the synthetic control approach has been previously used by Mideksa (2013) to estimate the impact of Norway's considerable petroleum endowment on economic growth. However, due to the cross-country nature of his application, the study cannot control for the likely presence of idiosyncratic shocks to individual countries. Our paper, to our knowledge, presents the first evaluation of both the local economic and environmental impact of natural resource abundance using the synthetic control approach in a within-country setting.

To assess the economic and environmental impacts of the Camisea Gas Project at the department level, we employ two sources of remote-sensing data. To measure economic activity, we rely on remotely sensed nightlight density, or luminosity, capturing human economic activity carried out during nighttime at considerably low levels of spatial disaggregation. The environmental effect of the program is measured in terms of deforestation rates, as captured by the Normalized Difference Vegetation Index (NDVI) processed from NASA's Land Long Term Data Record satellite imagery, which provides both sufficient spatial resolution to measure deforestation at the departmental level as well as a continuous time series dating back more than 20 years. The final dataset includes this information on a total of 25 departments for the period of 1992-2012. Using this data, we employ the synthetic control methodology to create a synthetic Cusco that represents a weighted average of all Peruvian departments and can mirror the

[7] The Canon Law of 2001 allocates royalties associated with the extraction of a number of different natural resources (e.g. gas, mining, oil, energy, fisheries, and forestry). Canon is a Spanish word commonly used in Peru to describe a rule by which a fraction of the natural resource revenues collected by the central government is allocated to subnational governments where the resources are found. The Canon Law thus regulates the distribution of resources in favor of municipalities and regional governments where the resources are located. Thus, Cusco as the region where the Camisea Gas Project's natural gas is located receives revenues through the Canon Law.

trajectory of luminosity and forest cover in the absence of treatment to assess the impact of the Camisea Gas Project on the economic and environmental development of Cusco.

Our analysis provides a positive image of the medium-term effects of this large-scale infrastructure investment. The results indicate that the Camisea Gas Project had a positive impact on local economic growth as measured by an annual gap of 27.9% in luminosity, or approximately 7.5% in local GDP between Cusco and its synthetic counterpart. Here, luminosity in Cusco exceeds the upper bound of the estimated 95% confidence intervals in five of the seven years post-treatment for the period 2007-2012. This suggests that royalty payments targeted towards the economic development of the department may have helped Cusco avoid falling into the trap of the natural resource curse. With regards to the environmental impact of the project, results are also encouraging. Despite the feared adverse effect on Cusco's pristine rainforest, our analysis does not detect significant negative effects, with the annual post-treatment gap between actual and synthetic Cusco remaining close to zero. This neutral impact result indicates that strict environmental and social safeguards may have played a significant role in preventing adverse ecological effects of the project on the surrounding area, and that encouraging economic growth without negative environmental consequences is possible if the latter is strictly monitored and regulated. It should be noted, of course, that the focus of the analysis is limited to the department of Cusco; Camisea's larger, potentially country-wide impacts go beyond the scope of this paper.

The remainder of the paper is organized as follows: Section 2 provides background information on the Camisea Gas Project, the Gas Canon Law, and the department of Cusco. Section 3 then describes the data set used and discusses in more detail luminosity as an impact indicator for economic growth and NDVI as an impact indicator for deforestation. Section 4 presents the methodological approach used and discusses potential empirical issues and how these are addressed. Results of the impact analysis and appropriate sensitivity tests are presented and analyzed in Section 5. Finally, Section 6 contains concluding notes and policy implications.

2 The Camisea Gas Project

The Camisea natural gas fields are located in the lower Urubamba region of the department of Cusco in southeastern Peru, an area of extraordinarily high biological diversity (Dallmeier & Alonso, 1997). It is also the home to indigenous peoples living in voluntary isolation. Camisea, with proven reserves of 9 trillion cubic feet, is among the largest in Latin America. Initially discovered in the 1980s, development of the Camisea natural gas fields was not launched until the late 1990s. In 2000, the Government of Peru (GoP) awarded the development of the fields to an "upstream" consortium led by the Argentinian oil company PlusPetrol, and a second, "downstream" consortium headed by the company TGP (Transportadora de Gas del Peru) was awarded the construction and operation of two major pipeline systems to transport the natural gas and natural gas liquids to Peru's coast (IDB, 2002).

TGP requested a US$75 million loan from the IDB, with the hope that the loan's approval would unlock other funding sources[8]. Prior to approval, the IDB carried out detailed environmental and social impact studies for the entire project. This process allowed environmental organizations to raise their concerns and participate actively in proposing risk mitigating actions by the project sponsors and the GoP. In parallel, the IDB granted a US$5 million institutional strengthening loan to the GoP to support its oversight of the project and to promote sustainable development in the area of influence of the Camisea project. The GoP for its part presented the IDB with a letter of "commitments" outlining specific actions it would undertake to deal with the direct, indirect and cumulative environmental and social impacts and risks associated with the Camisea Project, including assistance to governmental entities receiving project royalties, creation and resource allocation for new natural protected areas near the project, the creation of the Nahua Kugapakori Reserve for the protection of Indigenous Peoples Living in Voluntary Isolation, and enhanced environmental management planning (GoP, 2003).[9] These efforts led to significant modifications in the technology used for construction of the project, the introduction of measures to protect and safeguard the rich biodiverse and culturally sensitive area, and the promotion of sustainable development in Cusco and other regions. We now turn to describing the most important actions adopted as a result of the bargaining that took place among the GoP, the extraction firm, the IDB and environmental organizations.[10]

The extraction firm adopted a so-called "offshore" technology at Camisea: drilling sites were operated as if they were islands in the jungle (IDB, 2003). Workers and supplies were helicoptered in, and no access roads were built. These efforts were meant to minimize risks of colonization from the highlands and illegal extraction activities in the pristine rainforest. With the same

[8] Due to pressure from civil society groups over concerns about the project's environmental risks, some funding agencies, including the US Overseas Private Investment Corporation (OPIC), and the Export-Import Bank of the United States (Ex-Im) eventually decided not to provide funding for the project.

[9] One requirement associated with the IDB approval of the loan to TGP was for IDB Management to provide periodic reports to the IDB Board of Executive Directors summarizing the performance of TGP, Pluspetrol, and the GoP pertaining to their respective environmental and social commitments. In addition, progress made was closely monitored and reported to civil society in biannual workshops held in Peru and in Washington, DC (see https://www.iadb.org/en/project/pe0222 for specific reports of meetings held).

[10] The bargaining outcome seems consistent with the theoretical sequential Nash bargaining model of Schopf and Voss (2018), where the IDB served as a conduit and filter for the demands of environmental organizations. Once the Ex-Im Bank and other potential lenders dropped out, the bargaining position of the IDB was strengthened and the GoP and extraction firm were more receptive to the stringent safeguard and development proposals put forth.

objective in mind, the GoP created four new protected areas in the lower Urubamba, totaling close to a million hectares, or around 0.7% of the total Peruvian territory. Linked to this strategy was the safeguarding of native communities' territories in the buffer area of the Camisea Project. In this regard, the property rights of 33 communities were enhanced. One of the most contentious aspects of the project was that the Camisea gas fields where located in territories inhabited by IPLVI. As a response, the GOP created the Nahua Kugapakori Reserve, and implemented protocols with Pluspetrol to minimize potential contact. A compensation fund was also stablished. Realizing that Cusco would receive significant Camisea royalty payments (see below), the GoP supported the development of land use plans and sustainable development plans, including the identification and prioritization of projects. In parallel, the GoP launched an ambitious training program in public investment project management that trained over 370 professionals from local municipalities. Finally, the GoP supported local governments to develop feasibility studies of over 70 key projects for investment with royalty resources (IDB, 2008).

In sum, Camisea represents a unique kind of hydrocarbon project, not only in the sheer scale of its infrastructure, but also in its potential for adverse environmental impact and the extent of institutional effort to mitigate these risks by implementing stringent and comprehensive safeguards, and to promote a more efficient and expedited use of Camisea royalty resources in the producing region of Cusco.

Construction of the project was finalized by 2004 and it became operational in June 2004. Since 2004, the Camisea Gas Project has been the biggest producer of hydrocarbons in Peru and generated approximately $1.13 billion in public revenues for subnational governments between 2004 and 2009 (Munilla, 2010). The department of Cusco, where the natural gas fields are located, has been the beneficiary of royalty payments of approximately $300 million annually in transfers from the central government (ibid).

The distribution of the substantial fiscal revenues resulting from the Camisea Gas project falls under allocative rules determined by the federal Canon Law. Legislated in 2001, the law regulates the distribution of public revenues collected from extractive industries (mining, oil, energy, forestry, and fishery) by the central government to producing subnational municipalities (Ardanaz & Maldonado, 2016). The exact distribution to the regional and local governments in Cusco is determined by a provision in the law, which takes into account whether the respective province is a gas producer, and prioritizes districts and provinces based on an index that measures the levels of poverty and unsatisfied basic needs in each municipality (Munilla, 2010). The central government further imposes certain spending conditions on the Canon transfers, so that resources are used for capital expenses that invest in infrastructure and the provision of public goods. The Gas Canon transfers are then allocated according to the following rule: the producing district (Echarate) receives 10%; the regional government (Cusco) receives 25%; local governments in the producing province receive 25%; local governments in non-producing provinces and districts receive 40%.

To put these fiscal windfalls from the Gas Canon transfers into perspective, the department of Cusco had, on average, an annual revenue of US$550 million between 2005 and 2013 (INEI, 2018). Therefore, the transfer payments contributed approximately 58% to annual revenue and generally exceeded the annual current expenditures among municipalities at the district and provincial level (ibid). This suggests that the fiscal windfalls that the Camisea gas project generated would have a significant impact on government spending in the department of Cusco.

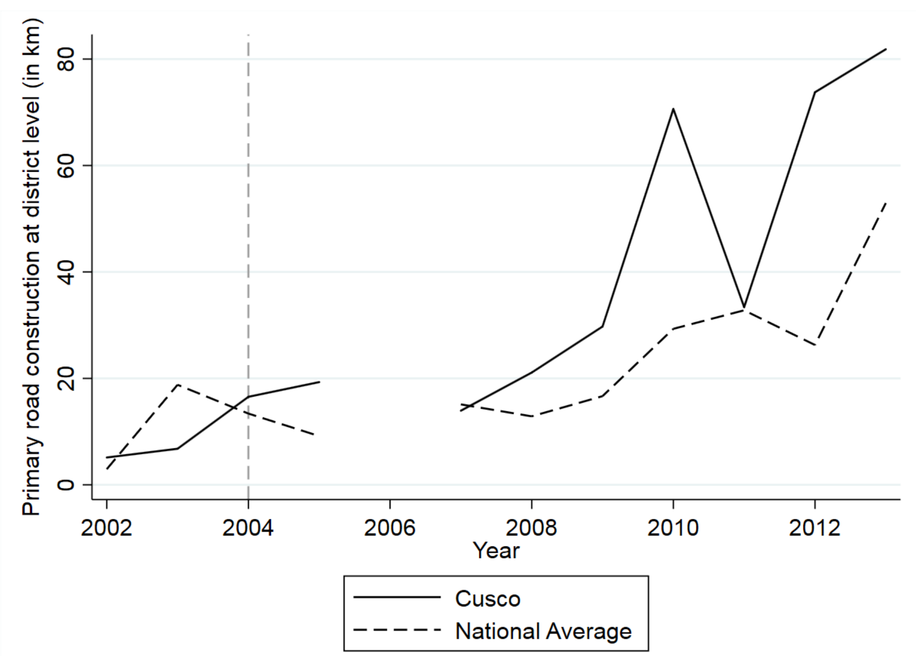

Figure 1. Primary road construction in Cusco in comparison to the national average.

To assess improvements in infrastructure that may have resulted from Camisea's natural resource windfalls to local governments, we consider the construction of new primary roads in Cusco in comparison to Peru's other departments.[11] We analyze data obtained from Peru's national register of municipalities, RENAMU (*Registro Nacional de Municipalidades*). Primary road construction reported at the district level was aggregated to department level for each

[11] Two departments were excluded from the comparison: Lima, due to its outlier characteristics as Peru's capital, and Ucayali, due to missing data. Therefore, the comparison is to the other 23 departments.

region.[12] Figure 1 displays the annual level of primary road construction between 2002 and 2013, comparing Cusco to the national average. Note that information for 2006 was not available from RENAMU.

As the graph indicates, annual road construction in Cusco has been higher than the national average level following the beginning of Camisea's operation in 2004. Between 2004 and 2013, an average of 40 km of primary road was constructed in Cusco, in comparison to only 23 km in other departments. This equals a total of 360 km of road constructed in Cusco in comparison to 208 km in other departments on average, implying that 73% more road was constructed in Cusco. This anecdotal evidence suggests that Gas Canon transfers may have indeed contributed to an expanding infrastructure and local economic development in Cusco.

3 Data Description

3.1 General Data Sources

To create a valid counterfactual for the department of Cusco with which to evaluate the impact of the Camisea Gas project on the economic development and environmental condition of Cusco, our study relies on a comprehensive panel dataset. For the synthetic Cusco to adequately mirror the trajectory of economic growth in the absence of the Camisea project, the dataset needs to contain variables that determine the level and trend of economic growth in each state, including socio-economic and infrastructural information. As indicated previously, the development impacts of natural resource windfalls depend crucially on the absorptive capacities of local governments. Therefore, the dataset also contains information on the budgetary flows and administrative capacity of municipal governments, at both the provincial and district level (since Canon transfers are distributed to both).

Specifically, we draw upon four data sources for the creation of our panel dataset. First, variables capturing socio-economic information at the department level are obtained from the *Sistema de Información Regional para la Toma de Decisiones* (SIRTOD). This database collects and systematizes information from various surveys conducted by Peru's national statistical agency INEI (*Instituto Nacional de Estadistica e Informatica*). From this database, we obtain annual information on regional variables including population size, dependency ratio, poverty rate, number of schools, health, and lodging facilities, as well as the number of construction licenses granted for new business establishments.

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[12] Since the data was reported in km^2, a rather unusual way of measuring the extent of road construction, the data was transformed into km using the assumption that primary, paved roads are on average 6m wide.

Second, we include additional information from INEI's national register of municipalities, RENAMU (*Registro Nacional de Municipalidades*), which has collected information on Peru's 1,842 municipalities (1,646 district and 196 provincial municipalities) at an annual frequency since 2002. Data in this register is self-reported by the municipality's administration and contains information on numerous topics ranging from district/province infrastructure and public services, to local development indicators in aspects of education, health, sanitation, public safety, as well as local economic activity. Variables selected from this database include the number of municipal staff at managerial, technical, and administrative level, current and capital expenditures and revenues, as well as the extent of the road network and access to public services within the jurisdiction. Though this information is available at the municipal level, the analysis is conducted at the department level, so that data is aggregated for all district and provincial governments within a department respectively.

The third and fourth sources of data for our panel data set provide information on the economic and environmental indicator, respectively, and are discussed in more detail below.

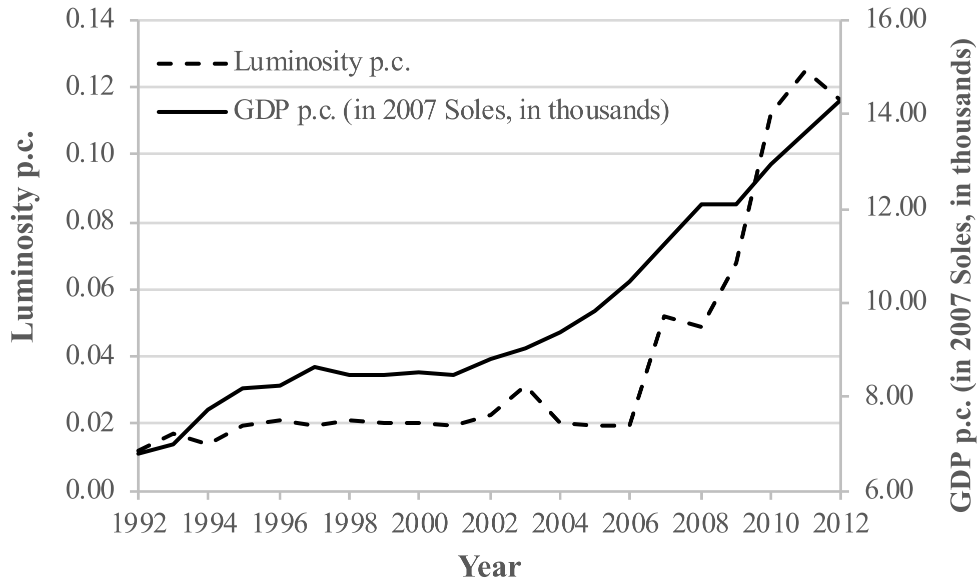
3.2 Luminosity as a Proxy of Economic Activity

Traditional measures of economic activity, such as the gross domestic product (GDP), the employment rate, or the investment rate, are not available at the department level for the time period preceding the Camisea Gas Project. While INEI systematizes and makes publicly available a plethora of economic indicators at the national and regional level, most regional-level data do not become available until after 2004. Since the synthetic control method relies crucially on the availability of a sufficiently long pre-treatment period to estimate a synthetic control that can fulfill the parallel trends assumption, none of these variables are a feasible option for our analysis.

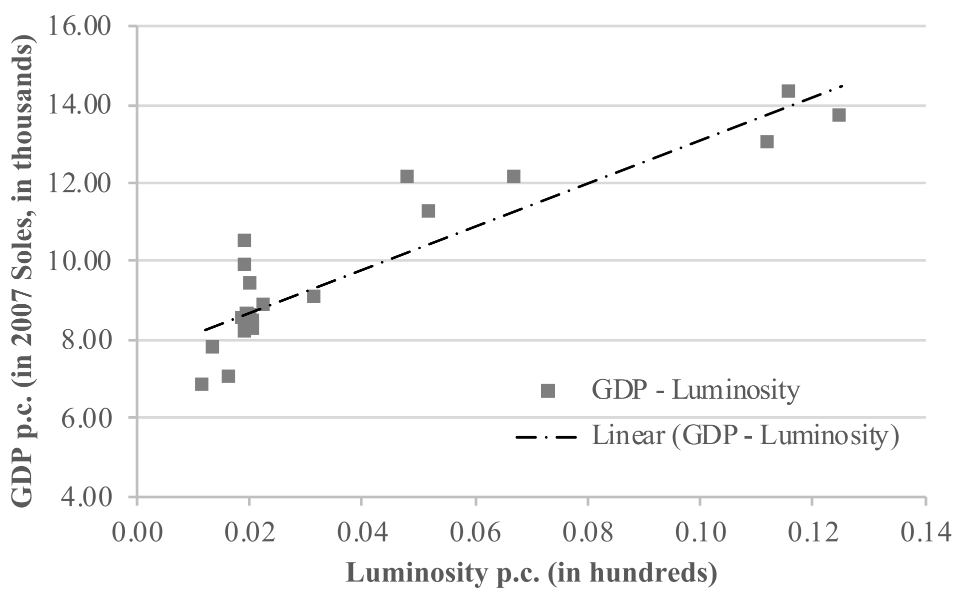
Given the unavailability of traditional measures of economic activity, the study relies on remotely sensed night light density data to approximate economic growth. Specifically, this night light density, or luminosity, data has been recorded since the 1970s by satellites from the United States Air Force Defense Meteorological Satellite Program, or DMSP for short, which use so-called Operational Linescan System (OLS) sensors to detect Earth-based lights (Henderson et al., 2012). In contrast to most other economic or demographic indicators that are based on estimates and censuses, light emission can be measured instantaneously, objectively, and systematically (Cauwels et al., 2014).

The raw data that becomes available from the satellites, which observe every location on the planet at a nightly interval, undergo extensive processing by the National Oceanic and Atmospheric Administration (NOAA) before being publicized. Light sources that may disturb the measurement of human-made luminosity, including forest fires, auroral activities, and extensive lunar light, are removed, and data is then averaged from all valid, cloud-cover free observations in a given year (Cauwels et al., 2014). The available satellite-year dataset reports intensity of lights in a latitude-longitude grid of 30 arc-second output pixels, which approximates 1 km^2 near the equator (ibid). Night light intensity is then represented as the index of an integer scale from 0 to 63, zero meaning no light and 63 being the most intense (Keola et al., 2015). To date, annual data is available from 1992 to 2012. The data is originally available in a grid of rectangular pixels of 30-arc seconds, where each pixel contains a luminosity index value that exhibits the annual average of night light intensity measured for this area. Since economic activity is to be measured at the department level, luminosity values for Peru are spatially aggregated from pixel to department level. Following the approach suggested in the literature (e.g., Zhou et al., 2015), each pixel located within the boundary of the department, even if only partially, is included in this aggregation. Our luminosity indicator then measures the annual sum of nightlights within each department.

Since NOAA made Earth-based lights captured by satellites publicly available in the early 1990s, an increasing number of papers have relied on luminosity as a proxy for income and GDP growth. Numerous studies, including those by Elvidge et al. (1997), Sutton and Costanza (2002), Doll et al. (2006), Ghosh et al. (2010), and Henderson et al. (2012) have corroborated the viability of night light intensity as a proxy for traditional measures of economic activity. Faced with a lack of reliable socioeconomic data, especially in developing countries, numerous authors have used luminosity to estimate economic growth at low levels of spatial disaggregation. For instance, Alesina et al. (2016) rely on nighttime light data combined with the historical location of ethnolinguistic groups to construct an index of ethnic income inequality in over 150 countries. Storeygard (2013) uses luminosity to investigate the effect of inter-city transport costs on urban economic activity in sub-Saharan Africa. In a study focusing on intra-city economic development, Agnew et al. (2008) assess the effect of the U.S. military surge into specific neighborhoods of Baghdad in 2007 on levels of violence and consequently the quality of life. In a recent study, Corral and Schling (2017) employ luminosity to evaluate the local economic impact of a shoreline stabilization program in Barbados.



(i) GDP and luminosity measures over time



(ii) Plotting GDP vs. luminosity measures

Figure 2. Luminosity as a measure of economic activity.

These and other studies have either shown or relied on the assumption that the intensity of night lights reflects both outdoor and indoor use of lights, which is required for consumption of almost all goods past nightfall. In this context, there appears to exist a positive, linear relationship between a rise in economic activity and greater lights usage per person (Henderson et al., 2012).

However, given that so many studies now rely on luminosity as a proxy for income and GDP growth, it becomes important to assess the relationship between these economic measures and their proxy where possible.

Panel (i) of Figure 2 depicts the time trend of GDP p.c. and luminosity p.c. at the country level for the period 1992-2012. The graph indicates that the rise of economic activity as measured by GDP reflects a slightly steadier increase, while luminosity is stagnant at first and then increases at faster rates after 2006. However, both time series exhibit a clear and similar upward trend. Plotting GDP versus luminosity, as displayed in Panel (ii), confirms this impression. The linear regression lines indicate that there exists a positive, linear relationship between the two variables. The R^2 of 0.82 for the linear regression suggests that luminosity can accurately capture variation in GDP. Lastly, the relationship between GDP and luminosity in terms of elasticity is also of interest. While the exact relationship varies by country context, reasonable estimates from the literature indicate an elasticity of around one between income and luminosity for most countries.[13] As presented in Appendix A, in the case of Peru a simple log-log regression indicates an elasticity of 0.27.

While the availability of GDP data at the national level allows us to assess the relationship between income and luminosity at the aggregate level, this might not necessarily hold for our analysis at the spatially disaggregated department level. We examine the relationship between luminosity and GDP for the department of Cusco for the six years between 2007 and 2012 for which both time series are available. Based on these six observations, there exists a strong positive correlation of 0.97 between the two variables, which suggests that a similar relationship may hold at the department level as it does at the national level. Nevertheless, the interpretation of results based on luminosity to assess changes in economic activity in Cusco will be done keeping in mind that the elasticity between GDP and luminosity may differ at the department level from the one estimated for Peru as a whole. Lastly, to interpret any change in luminosity over time in percentage terms, the natural logarithm of the luminosity per capita data is used as the impact indicator of interest in this evaluation.

3.3 Vegetation Index as a Proxy of Deforestation

To capture the environmental impact of the Camisea Gas Project on deforestation rates in Cusco, we use remote-sensing satellite imagery from NASA's Land Long Term Data Record (LTDR) over

[13] For country-specific estimates, please see Elvidge et al. (1997) or Henderson et al. (2012). Others, such as Sutton and Costanza (2002) or Ebener et al. (2005) find a high correlation between GDP measures and luminosity.

the period 1992-2012. Specifically, we rely on satellite data with a global 0.05-degree resolution which provides a measurement of vegetation through the *Normalized Difference Vegetation Index* (NDVI)[14]. This index measures the difference between near-infrared light and red light reflected from plants. It ranges from minus one (-1) to plus one (+1), where values below zero indicate no vegetation (or rocky terrain) and values close to one indicate a highly green area (or densely forested terrain).[15] As argued by BenYishay et al. (2017), while there are tradeoffs to using LTDR in lieu of other satellite datasets, the LTDR data record provides two key attributes, which makes the NDVI a good instrument to measure deforestation. First, the differences in NDVI values between forested and deforested lands are quite large: areas of barren rock or snow have usually very small NDVI values, whereas grasslands or tropical forests have moderate or high NDVI values. This feature from the NDVI allows us to capture changes in vegetation including deforestation.[16] Second, the daily time records extending back over nearly 30 years permit to rule out quality issues. This is a key attribute, given the importance of sufficient pre-treatment records necessary for the credibility of our synthetic control. In another application, Wyman and Stein (2010) also rely on the NDVI to assess the drivers of deforestation at the household level in protected areas of Belize.

To calculate yearly NDVI values at the department level, we processed 7,671 images of LTDR Version 4 (daily records of processed satellite information from the AVH13C1 satellite) for the minimum rectangle that encloses Peru.[17] We then constructed annual measures of the NDVI by analyzing the 194,081 cells contained in each daily raster file. To do so, we followed the approach used by BenYishay et al. (2017) and truncated the negative values to zero as they could represent water, snow, ice, dirt, or rock terrain. Hence, we calculated NDVI yearly values by aggregating the daily to monthly raster files using the maximum value per cell. Once again following the approach used by BenYishay et al. (2017), we use the maximum in lieu of the median because it approximates the highest point or observable plant productivity in any given month, thereby

[14] We recognize that other environmental impacts associated with Camisea, including on biodiversity, hunting, fishing, is not be captured by NDVI.

[15] See Appendix C for a more in-depth explanation of how vegetation is measured with this index.

[16] We did not make use of tree cover loss data from the University of Maryland (Hansen et al., 2013) as a proxy of deforestation for two reasons: First, one of the main drawbacks of this indicator is that it could unambiguously be related to other type of forest cover change – and not necessarily deforestation –, such as shifting patterns of cultivation by local communities, crop rotation, fire and storm damages or even selective logging. Second, recall that tree cover is defined as all vegetation taller than 5 meters in height, thus, as it has been pointed out by Mitchard et al. (2015), it might be the case that in certain areas of the country small areas of deforestation dominate, thus, if we were to use this indicator we might be underestimating the level of deforestation.

[17] These images were provided by the Land Data Operational Products Evaluation Team from NASA in a hdf format. Once the images were received, they were converted into raster files (.tif files) using standard statistical software.

providing the best measurement of total annual vegetation. We then aggregated to yearly raster files by finding the mean values per cell over the monthly raster files. This is done to average out the effect of extreme values from any given month. Finally, we extract yearly values for each department using the average value in the cells corresponding to each department polygon in Peru. During the image processing work, we found some daily images unclear due to excessive cloud coverage. This was particularly evident for 1994 images, where more than 100 images were completely blurred. To avoid potential data error in the NDVI calculation, we exclude data prior to 1995 from our analysis.[18]

In sum, by combining all described data sources, the final dataset is then a panel consisting of 21 years (1992-2012) for the luminosity indicator and 18 years (1995-2012) for the NDVI measure, for the 25 departments of Peru. In the following, we describe the methodology used to assess the impact of the Camisea Gas Project on economic development, as captured by night light density, and deforestation rates, as captured by the NDVI.

4 Constructing a synthetic version of Cusco and estimating impact

In this section, we describe the methodology used to assess the impact of the Camisea Gas Project on economic development, as captured by night light density, and deforestation rates, as captured by the NDVI. The impact evaluation of the Camisea Gas Project requires the identification of a valid counterfactual, i.e. what would have happened in the department of Cusco in the absence of this large-scale infrastructure project. Measuring this impact requires the estimation of the counterfactual outcome from sufficiently similar comparison units (departments). In this study, we utilize an empirically rigorous and data driven approach to choose the best comparison units by employing the synthetic control method of Abadie and Gardeazabal (2003). Ferrero and Hanauer (2014) highlight the potential of the synthetic control method to assess the impact of environmental programs. Sills et al. (2015) use the method to assess the impact of municipal level policy innovations in Brazil to stem deforestation; Mideksa (2013) created a synthetic control at the country level to estimate the impact of Norway's considerable petroleum endowment on economic growth.

For the construction of a synthetic control unit, Abadie and Gardeazabal (2003) propose that longitudinal data can be used to build a weighted average of non-treated units that best parallels characteristics of the treatment unit over time, prior to treatment. Abadie et al. (2010) highlight that the synthetic control approach has several methodological advantages over the more

[18] A step by step description of NDVI data processing can be found in Appendix B.

commonly used difference-in-difference approach, as its prominent features include both transparency and safeguarding against issues of extrapolation (ibid). Specifically, using a weighted average of all potential control units makes transparent the relative contribution of each unit to the counterfactual, and reveals similarities between treated and synthetic control units with respect to the important common trend assumption prior to the intervention (ibid). Furthermore, since individual weights are usually restricted to be positive and sum to one, extrapolation can purposefully be guarded against.

The creation of a synthetic control unit that most resembles the treatment unit in key pre-treatment characteristics crucially relies on $\boldsymbol{W} = (w_1, \dots, w_J)'$, a $(Jx1)$ vector of nonnegative weights for all potential control units J, where w_j represents the weight for unit j of the synthetic control, and all individual weights sum up to one. Let $\boldsymbol{X_1}$ be a $(K\ x\ 1)$ vector of K pre-treatment covariates of determinants of our outcome of interest (luminosity and deforestation in our case) for the treatment unit, in this case Cusco, and $\boldsymbol{X_0}$, a $(K\ x\ J)$ vector of the same variables for all possible control departments. Additionally, define $\boldsymbol{V}$ as a diagonal matrix with nonnegative values reflecting the relative importance of the different covariates. Then, the vector of optimal weights $\boldsymbol{W}^*$ is found by minimizing the distance in pre-treatment characteristics between treated units and the weighted average of control units:

$$\min_{\boldsymbol{W}} (\boldsymbol{X_1} - \boldsymbol{X_0 W})' \boldsymbol{V} (\boldsymbol{X_1} - \boldsymbol{X_0 W})$$

$$s.t.\ w_j \geq 0,\ \ w_1 + \cdots + w_J = 1 \qquad \forall\, j = 1,2,\dots,J$$

Note that for the diagonal matrix $\boldsymbol{V}$, components are optimally chosen to linearly weigh variables of $\boldsymbol{X_0}$ and $\boldsymbol{X_1}$ so that the mean square error of the synthetic control estimator is minimized, which can be achieved, for instance, by choosing $\boldsymbol{V}$ such that the mean squared prediction error (MSPE) of the outcome variable is minimized for pre-treatment periods (ibid).

The estimated treatment effect $\hat{\alpha}_{0t}$ on an outcome Y (luminosity and deforestation in our case) over the period $t \in \{T_0 + 1, \dots, T_1\}$ for an intervention that occurred in time T_0 is then the difference between the observed outcome of the treated unit ($j = 0$) and the weighted average of outcome values for control units:

$$\hat{\alpha}_{0t} = Y_{0t} - \sum_{j=1}^{J} w_j^* Y_{jt}$$

The estimated impact is computed by measuring the ex-post difference between the outcome of an indicator in the treatment unit, Y_{0t}, and the outcome for the synthetic control unit as an optimally weighted average of all control units in the donor pool, $\sum_{j=1}^{J} w_j^* Y_{jt}$. In this context, the choice of pre-treatment characteristics crucially determines the weights and composition of the synthetic control. Therefore, one should choose that specification for which included pre-treatment characteristics generate the smallest mean squared prediction error (MSPE) that can be achieved to find the optimal weight distribution (Abadie & Gardeazabal, 2003).

We take advantage of the twelve pre-treatment years (1992-2003) of available luminosity data and nine years (1995-2003) of deforestation data to construct a synthetic Cusco that mirrors the levels of economic activity, as captured by luminosity, and deforestation as captured by NDVI prior to the beginning of operations of the Camisea Gas Project and the royalty payments to the department of Cusco in 2004. Pre-treatment characteristics that are posited to be determinants of luminosity and deforestation are chosen based on the previous discussion and include socio-economic characteristics (population size, poverty and dependency rate, number of health facilities, schools, and business licenses), infrastructure (road network, household access to water network), as well as the municipal absorptive capacity (number of staff) and budgetary flows at both the provincial and district level. Following the approach suggested by Kaul et al. (2016), we include the average of all pre-treatment luminosity values as an additional predictor.

Since the purpose of the synthetically created control unit for Cusco is to reproduce the luminosity and deforestation values that would have occurred in Cusco if the Camisea Gas Project had not been undertaken, both the department and independent province of Lima are a priori discarded from the donor pool, since they differ significantly from the rest of the country. The department of Ucayali was also excluded, since a significant share of data was not available for this region. This leaves us with a total of 22 departments in the donor pool.

Because we have one treatment unit and relatively few comparison units in the donor pool, the optimal synthetic control is potentially a noisy estimate of the counterfactual and we cannot rely on large-sample properties to provide standard errors for statistical assessment. To address this limitation, we evaluate the statistical significance of the post-treatment impact by estimating standard errors based on a bootstrapping method previously used by Kirkpatrick and Bennear (2014), Sills et al. (2015), and Corral and Schling (2017). We construct 1,000 synthetic controls from a subset of 15 departments iteratively and randomly drawn (without replacement) from the final donor pool of 22 departments. The estimated **W** weights from each of the 1,000 iterations are then used to create 95 % confidence bounds on the estimated median synthetic Cusco.

The economic (environmental) impact of the Camisea Gas Project is estimated as the difference in actual luminosity p.c. (NDVI) levels in Cusco against those predicted by synthetic Cusco, including the 95% confidence bounds on the estimated counterfactual, during the post-treatment period of 2005-2012. Robustness checks consisting of sensitivity and falsification tests are also performed and reported below.

5 Results

5.1 Economic Impact

Turning first to the economic impact of the Camisea Gas Project as measured by luminosity, we construct a synthetic Cusco from a convex combination of departments in the donor pool. Table I displays the mean values of all pre-treatment characteristics for actual and synthetic Cusco, as well as the average values for the entire study area. The last column presents the optimal weight distribution for included covariates (as captured in the diagonal matrix $\boldsymbol{V}$). Based on the study area averages, it becomes clear that not all departments in the donor pool would have provided a reasonable counterfactual for the department of Cusco. Average levels of luminosity in Peru are higher than in Cusco, which appears reasonable given the remote location of Cusco and the fact that it remained one of the poorest departments of the country.

This is also reflected in several department-level covariates, which indicate that on average, households in Cusco had a higher dependency ratio of children and seniors to working-age adults in households, a significantly lower number of health-related facilities. In contrast, the number of new establishments and small and medium enterprises in the state seemed to lie above the study area average. In terms of province- and district-level attributes, the summary statistics indicate that municipal governments within donor pool states counted with higher levels of revenues and expenditures, though with slightly less municipal white-collar staff. Primary road construction, as an indicator of investment in infrastructure, appeared higher within the districts of donor pool departments.

Table I. Luminosity: Pre-treatment characteristics (1992-2003 average).

Variable	*Study Area*	Cusco		*V Matrix Weights*
		Actual	*Syntheti c*	
Luminosity per 10,000 people, logged	5.72	5.12	5.12	0.00
Population (in 10,000s, avg. 1994-2003)	78.73	115.99	98.45	0.00
Department-level characteristics				
Dependency ratio (1993)	71.29	83.80	81.59	0.00
No. of health-related facilities (2000-2003)	257.44	130.25	143.74	0.00
No. of licenses granted for opening establishments (in 1000, 2003)	1.52	3.60	2.32	0.00

No. of licenses granted for opening restaurants (in 1000, 2003)	0.15	0.74	0.19	0.00
Small and medium enterprises of food and beverages (2003)	216.09	693.00	303.05	0.00
Personnel (in 10,000, 2003)	0.20	0.31	0.28	0.02
Aggregated Province-level characteristics				
Managerial municipal staff per 10,000 people (2003)	1.41	0.78	1.68	0.00
White-collar municipal staff per 10,000 people (2003)	1.16	1.55	1.13	0.00
Technical municipal staff per 10,000 people (2003)	3.92	3.67	3.43	0.00
Municipal revenue per capita (in PEN, 2003)	83.65	69.91	74.06	0.03
Municipal expenditures per capita (in PEN, 2003)	72.98	71.80	68.25	0.01
Primary roads constructed (in km^2, 2003)	0.03	0.04	0.04	0.00
Aggregated District-level characteristics				
Managerial municipal staff per 10,000 people (2003)	1.13	1.19	1.24	0.00
White-collar municipal staff per 10,000 people (2003)	1.97	2.67	1.69	0.00
Technical municipal staff per 10,000 people (2003)	4.17	4.02	3.99	0.00
Municipal revenue per capita (in PEN, 2003)	155.38	77.72	93.11	0.65
Municipal expenditures per capita (in PEN, 2003)	112.41	98.54	80.94	0.25
Primary roads constructed (in km^2, 2003)	0.14	0.05	0.16	0.00

In contrast, synthetic Cusco is able to reproduce more accurately the average pre-treatment values for key characteristics capturing the departments economic activity, infrastructure, and government finances and employment. Some characteristics, notably the number of small and medium enterprises of food and beverages, are not reproduced as accurately. However, a look at the V matrix weights reveals that these variables received a weight approaching zero in the optimization, as they do not appear to have substantial predicting power with regards to pre-treatment luminosity levels.

Table II displays the distribution of the optimal weights estimated for each department in the donor pool to create a synthetic Cusco. In the specification that renders the best fit (as expressed in the smallest mean squared prediction error, or MSPE), synthetic Cusco is composed of seven departments. Interestingly, the geographic location of these departments is not limited to one region of Peru, say the jungle, mountain, or coastal region. Rather, the departments that contribute to synthetic Cusco are distributed throughout the country, from Piura as the northernmost coastal state, to Loreto as Peru’s largest state located in the Amazonian rainforest.

Table II. Luminosity: Optimal department weights for synthetic Cusco.

Department	*Weight*	*Department*	*Weight*
Amazonas	0	Lambayeque	0
Ancash	0	Lima	-
Apurímac	0.193	Loreto	0.164
Arequipa	0	Madre de Dios	0
Ayacucho	0	Moquegua	0
Cajamarca	0	Pasco	0
Callao	0.195	Piura	0.185
Huancavelica	0	Puno	0
Huánuco	0	San Martin	0.001
Ica	0	Tacna	0
Junín	0.218	Tumbes	0
La Libertad	0.044	Ucayali	-

Having constructed a synthetic counterfactual that adequately reproduces pre-treatment luminosity levels in Cusco, the post-treatment impact for 2005-2012 can now be estimated. Figure 4 depicts actual luminosity for Cusco and the 95% confidence bounds on the estimated synthetic counterfactual. The graph displays the period 1992-2012, where the treatment occurring in 2004 is indicated by the vertical dotted line. As the graph indicates, economic growth as measured by luminosity remained relatively modest in the years prior to 2004. A comparison of the trend in Cusco to that of median Cusco and the confidence bounds prior to the inception of Camisea suggests that our synthetic control specification can indeed replicate the pre-treatment trajectory of the treated unit. Notably, luminosity in Cusco experiences a modest peak in the year 2003, which is accurately captured by the trend line for synthetic Cusco.

The impact of the Camisea Gas Program on economic activity in Cusco is measured as the estimated difference between luminosity in actual and synthetic Cusco. As can be seen in Figure 4 below, the two lines begin to diverge following an initial dip in luminosity during the first two years post-treatment. Beginning in 2006, economic activity in Cusco increases drastically, and while this significant economic growth appears to be part of a general trend, synthetic Cusco does not exhibit the same increases as observed in Cusco. In 2007 and thereafter, we observe an ever-widening positive gap between Cusco and synthetic Cusco, which also exceeds the upper confidence bound between 2007 and 2012.

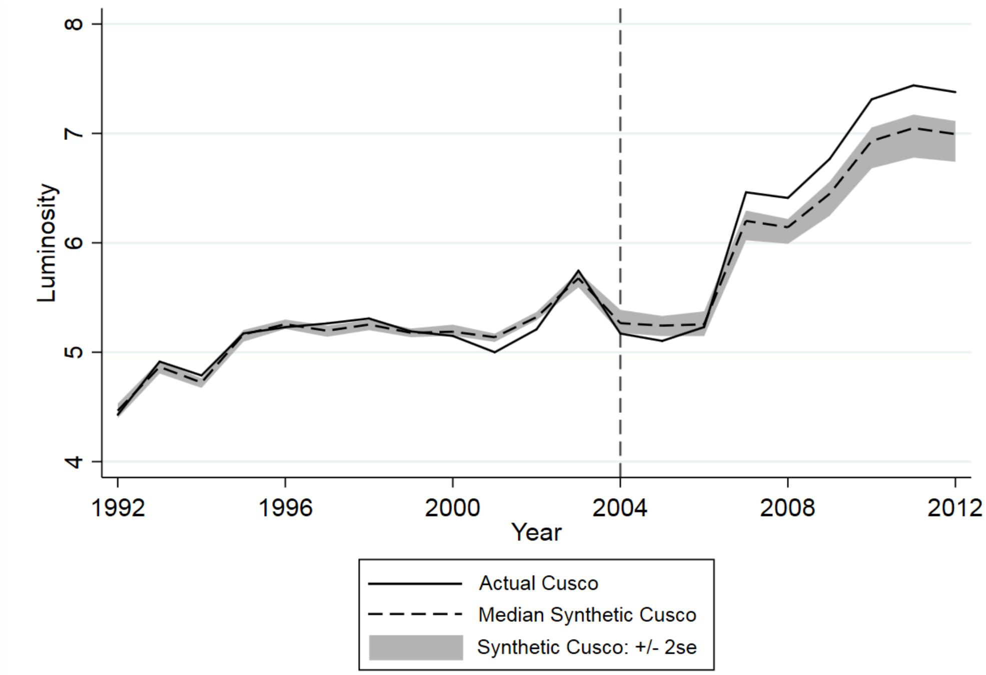


Figure 4. Luminosity for Cusco and synthetic Cusco.

This impact gap is illustrated in Table III, which presents the annual post-treatment difference in luminosity between Cusco and the best-fit synthetic Cusco. Note that because luminosity has been transformed to natural logarithms, the difference between actual and synthetic Cusco can be interpreted in percentage terms. Therefore, the estimated gap confirms the visual interpretation of a consistent positive impact beginning in 2007: Ranging from 33.7 % in 2007 to 50 % in 2011, the post-treatment gap can be quantified at an average annual increase of 27.9 % in luminosity. Given that luminosity in Cusco exceeds the upper confidence bound of synthetic Cusco for the last six years post-treatment, this suggests that the impact gap is indicative of a significant effect of the Camisea Gas Project for these years.

Given that the exact relationship between luminosity and GDP cannot be determined at the department level due to the lack of data, we use the elasticity of luminosity and GDP at the national level, estimated to be 0.27, to approximate the impact on local economic activity. Using this elasticity, an average annual post-treatment gap of 27.9 % in luminosity would therefore imply that local GDP increased, on average, by an annual 7.5 % between 2005 and 2012.

Table III. Gap in luminosity.

Year	**Gap**	**Actual Cusco**	**Synthetic Cusco: 95% Confidence Interval**

			Low	*High*
2005	**-0.200**	5.103	5.197	5.326
2006	-0.125	5.230	5.167	5.372
2007	**0.337**	6.462	6.006	6.278
2008	**0.351**	6.411	5.969	6.204
2009	**0.396**	6.768	6.224	6.540
2010	**0.482**	7.312	6.648	7.033
2011	**0.500**	7.440	6.727	7.153
2012	**0.489**	7.378	6.703	7.095

Overall, this suggests that the large-scale infrastructure investment and subsequent receipts of gas royalties from the Camisea Gas Project have had a positive impact on local economic activity in Cusco in comparison to what would have been experienced without the Project. While these impact estimates based on the synthetic control approach appear promising, it is possible that these results are driven by some alternate explanation, rather than a significant effect of the Camisea Gas Project. To assess whether the results are robust, a number of placebo tests that follow Abadie et al. (2003; 2010) and others are conducted.[19]

The first robustness check reviews the choice of optimal weights in the diagonal matrix V. While the synthetic control process ensures that covariate weights assigned through V are chosen so that the mean squared error of the synthetic control estimate is minimized, it is still possible that the optimal choice of V is affected by the researcher's subjective assessment of the predictive power of individual covariates included in the specification (Abadie et al., 2003).

[19] In addition to the robustness checks presented here, Appendix D includes an additional falsification test.

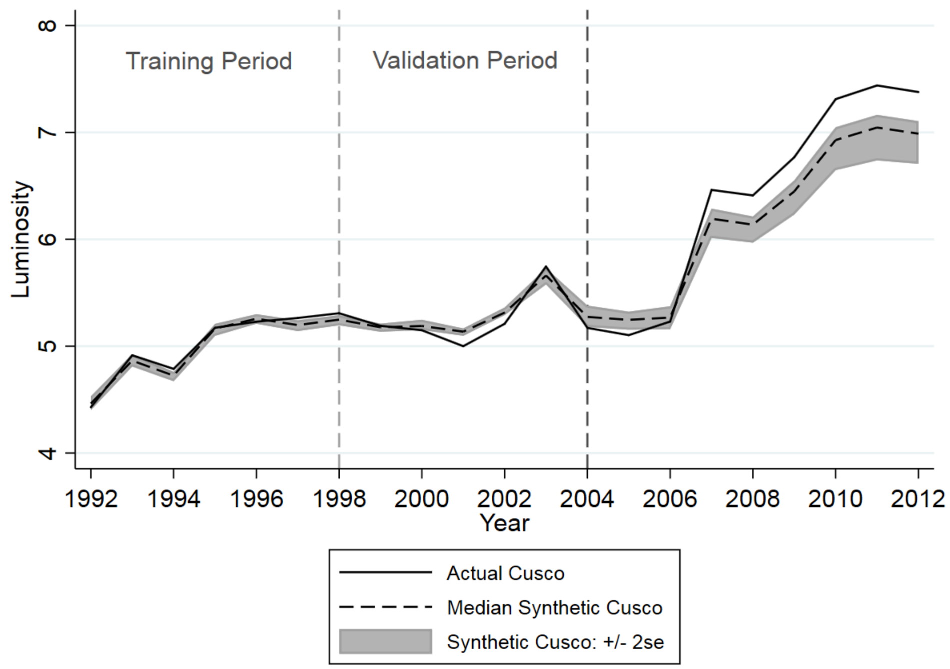


Figure 5. Constructing a synthetic control using cross-validation for luminosity.

To confirm that this method still renders the best fit for the available data, Abadie et al. (2010) proposes a method of cross-validation, dividing the time before treatment into a “training period” and a “validation period”. If an optimal fit is found for the initial “training period”, the synthetic control should mirror as closely as possible the movement of luminosity in actual Cusco during the “validation period”, because no treatment has yet occurred that could let actual and synthetic Cusco diverge. If this is achieved, the chosen matrix V can then be used to compute optimal covariate weights to create a synthetic control that has proven accurate in mirroring the actual data trend and now extends through the post-treatment time period.

Figure 5 presents the results of creating a synthetic Cusco using this alternative cross-validation method. Bootstrapped confidence bounds are computed to assess the fit of the synthetic control for this specification. The year 1998 is chosen as the cut-off point that divides the pre-treatment period into training and validation period. Synthetic Cusco achieves a similar fit during the validation period of 1999-2004 to that of the optimization approach presented in Figure 4. The trajectory obtained for the post-treatment period appears similar to that in Figure 4 and is of similar magnitude.

Table IV. Gap and confidence bounds with cross validation method for luminosity.

Year	Gap	Actual Cusco	Synthetic Cusco: 95% Confidence Interval	
			Low	*High*
2005	**-0.199**	5.103	5.154	5.322
2006	-0.127	5.230	5.159	5.373
2007	**0.334**	6.462	6.013	6.287
2008	**0.347**	6.411	5.969	6.213
2009	**0.392**	6.768	6.232	6.551
2010	**0.471**	7.312	6.648	7.048
2011	**0.485**	7.440	6.738	7.164
2012	**0.476**	7.378	6.706	7.106

Table IV presents the estimated impact gap alongside 95 % confidence bounds around median synthetic Cusco computed with the cross-validation method. The confidence bounds are very similar to those created for the original specification, so that the estimated annual gaps in luminosity are of very similar magnitude. These gaps lie outside of the confidence bounds in the same years as before, with a slightly negative significant gap in 2005, and consistently positive significant impacts for the years 2007-2012, though annual post-treatment gaps are slightly smaller for the cross-validation method. This results in an average annual gap of 27.2 % in deblurred luminosity, or a corresponding 7.3 % average annual increase in local GDP.

Another concern is that results are driven by one particular control unit that strongly determines the trajectory of synthetic Cusco, potentially due to the particular characteristics of that department. Following the approach in Mideksa (2013), departments that received positive weights in the original synthetic control specification are sequentially removed from the estimation. Table V displays the resulting gaps and confidence bounds, where the relevant seven donor pool departments were sequentially excluded from the estimation. A visual representation of the sensitivity test can be found in Appendix A.

The results of this test are consistent with the main result in two regards: First, confidence bounds for each of the seven specifications are very similar to those estimated for the original model. Second, luminosity values for Cusco consistently exceed the upper confidence bound for five of seven post-treatment years (2007-2012), and the lower confidence bound for the first year post-treatment, 2005. The estimated annual gaps vary in magnitude to some degree, with an average annual post-treatment gap of 14.2 % in luminosity (3.8 % in GDP) when Apurímac is excluded, to a 28.8 % in luminosity (7.8 % in GDP) if La Libertad is excluded from the donor pool. Given that the original specification rendered a result of 27.9 % in luminosity (7.5 % in GDP), this sensitivity analysis suggests that this may be an upper bound estimate of the economic impact, and that the actual effect on local economic growth may have been slightly smaller, though still economically significant.

Table V. Sensitivity test with bootstrapped confidence bounds for luminosity.

		Without Apurímac			Without Callao			Without Junín			Without La Libertad		
			95% CI around Cusco			95% CI around Cusco			95% CI around Cusco			95% CI around Cusco	
Year	*Actual Cusco*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*
2005	5.103	**-0.140**	5.227	5.336	**-0.130**	5.202	5.347	**-0.108**	5.172	5.331	**-0.050**	5.164	5.325
2006	5.230	0.026	5.197	5.386	-0.012	5.168	5.388	-0.005	5.193	5.407	0.044	5.164	5.371
2007	6.462	**0.152**	6.066	6.286	**0.256**	6.073	6.335	**0.288**	5.974	6.259	**0.289**	6.025	6.282
2008	6.411	**0.179**	6.028	6.214	**0.266**	6.037	6.256	**0.277**	5.955	6.203	**0.277**	5.989	6.204
2009	6.768	**0.190**	6.294	6.551	**0.302**	6.316	6.603	**0.347**	6.203	6.527	**0.364**	6.249	6.549
2010	7.312	**0.237**	6.731	7.044	**0.345**	6.776	7.085	**0.413**	6.615	7.030	**0.446**	6.676	7.038
2011	7.440	**0.247**	6.820	7.167	**0.349**	6.884	7.200	**0.434**	6.687	7.158	**0.476**	6.766	7.160
2012	7.378	**0.245**	6.781	7.102	**0.347**	6.837	7.149	**0.423**	6.665	7.091	**0.455**	6.729	7.099
		Without Loreto			**Without Piura**			**Without San Martin**					
			95% CI around Cusco			95% CI around Cusco			95% CI around Cusco				
Year	*Actual Cusco*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*			
2005	5.103	**-0.107**	5.200	5.327	**-0.101**	5.184	5.334	**-0.102**	5.170	5.246			
2006	5.230	0.056	5.175	5.377	0.062	5.161	5.366	0.061	5.167	5.264			
2007	6.462	**0.211**	6.030	6.295	**0.217**	6.006	6.327	**0.216**	5.966	6.188			
2008	6.411	**0.237**	5.993	6.221	**0.243**	5.968	6.253	**0.243**	5.942	6.133			
2009	6.768	**0.256**	6.260	6.558	**0.262**	6.220	6.599	**0.262**	6.195	6.438			
2010	7.312	**0.308**	6.688	7.045	**0.315**	6.617	7.084	**0.314**	6.649	6.910			
2011	7.440	**0.319**	6.777	7.159	**0.326**	6.686	7.198	**0.326**	6.754	7.025			
2012	7.378	**0.309**	6.739	7.105	**0.316**	6.662	7.147	**0.316**	6.714	6.973			

Overall, the results of this analysis indicate that, within a few years of the Camisea gas fields beginning operation, a consistently meaningful and significant impact can be found on the local economic activity in Cusco as measured by luminosity. This suggests that this large-scale infrastructure project and subsequent natural resource windfalls via royalty transfers has had a positive impact on economic development in the medium term, and that Cusco has, to some extent, avoided the pitfalls associated with the natural resource curse.

5.2 Environmental Impact

We now turn to assessing whether this economic growth came at the cost of incremental environmental degradation as captured by deforestation. We again employ the synthetic control approach. Table VI presents the mean values of all pre-treatment characteristics for departments in the donor pool as well as for Cusco and its synthetically created counterpart.[20] The last column again presents the optimal weight distribution for included covariates in the diagonal matrix $\boldsymbol{V}$ that is used to compose synthetic Cusco.

Table VI. NDVI: Pre-treatment characteristics (1995-2003 average).

Variable	*Study Area*	Cusco		*V Matrix Weights*
		Actual	*Synthetic*	
Normalized Difference Vegetation Index (NDVI)	0.40	0.48	0.48	0.69
Population (in 10,000s, avg. 1995-2003)	5.71	5.25	5.46	0.00
Department-level characteristics				
No. of licenses granted for opening restaurants (in 1000, 2003)	1.77	3.60	1.84	0.00
Personnel (in 10,000, 2003)	0.21	0.31	0.23	0.00
Aggregated Province-level characteristics				
Managerial municipal staff per 10,000 people (2003)	1.37	0.78	1.53	0.00
White-collar municipal staff per 10,000 people (2003)	1.20	1.55	1.04	0.00
Municipal revenue per capita (in PEN, 2003)	84.56	69.91	69.14	0.05
Municipal expenditures per capita (in PEN, 2003)	73.28	71.80	61.92	0.00
Aggregated District-level characteristics				
Managerial municipal staff per 10,000 people (2003)	1.15	1.19	1.20	0.00
White-collar municipal staff per 10,000 people (2003)	2.00	2.67	2.55	0.02
Municipal revenue per capita (in PEN, 2003)	147.69	77.72	104.78	0.05
Municipal expenditures per capita (in PEN, 2003)	110.13	98.54	94.86	0.11
Primary roads constructed (in km^2, 2003)	0.16	0.49	0.64	0.05

This exercise again provides a justification for choosing synthetic Cusco as a counterfactual over a simple study area average: Departments in the donor pool appear to have less vegetation and higher population. Municipal governments enjoy significantly higher revenues at both the district and province level, as well as having slightly higher expenditures. In comparison, synthetic Cusco is able to reproduce the same level of vegetation as measured for Cusco during the pre-treatment period, and closely resembles the treated department across covariates such as

[20] It should be noted that additional covariates to capture agricultural activity as a determinant of deforestation were not available for the pre-treatment period and/or for all control units, so that they had to be excluded from the analysis.

municipal revenue and expenditure and the number of municipal government staff. These are the variables that also receive significant weight in the V-matrix and therefore contribute considerably to identifying departments that contribute to creating a synthetic Cusco.

Table VII. NDVI: Optimal department weights for synthetic Cusco.

Department	*Weight*	*Department*	*Weight*
Amazonas	0	Lambayeque	0
Ancash	0	Lima	-
Apurímac	0	Loreto	0.162
Arequipa	0	Madre de Dios	0
Ayacucho	0	Moquegua	0.07
Cajamarca	0.137	Pasco	0
Callao	0	Piura	0
Huancavelica	0.168	Puno	0
Huánuco	0	San Martin	0
Ica	0	Tacna	0.006
Junín	0.458	Tumbes	0
La Libertad	0	Ucayali	-

Table VII displays the distribution of the optimal weights estimated for each department in the donor pool to create a synthetic Cusco with regards to its pre-treatment NDVI trend. In the specification with the lowest mean squared prediction error (MSPE), synthetic Cusco is composed of six departments. Here, four of the six departments are located in the climatic zones of the highlands (Cajamarca, Huancavelica, and Junín) and jungle (Loreto), while only two are located along the coastal line of Peru (Moquegua and Tacna) with relatively small weights. Given the focus on vegetation density to create synthetic Cusco, it is therefore not surprising that departments in the highlands and jungle with larger green areas would contribute more to the counterfactual. In a next step, the NDVI trend in Cusco is compared visually to the trajectory of the synthetic counterfactual. Figure 6 presents this visualization, including the median synthetic control as well as bootstrapped 95% confidence bounds. Once again, the vertical dotted line indicates the occurrence of treatment when operation at the Camisea gas fields began. NDVI levels remained relatively stable in Cusco in the displayed time period of 1995 to 2012. Given the low volatility of pre-treatment trends, we are able to closely mirror the trajectory of NDVI in Cusco with the synthetic counterfactual, with the median synthetic control overlaying actual Cusco for most of the pretreatment period.

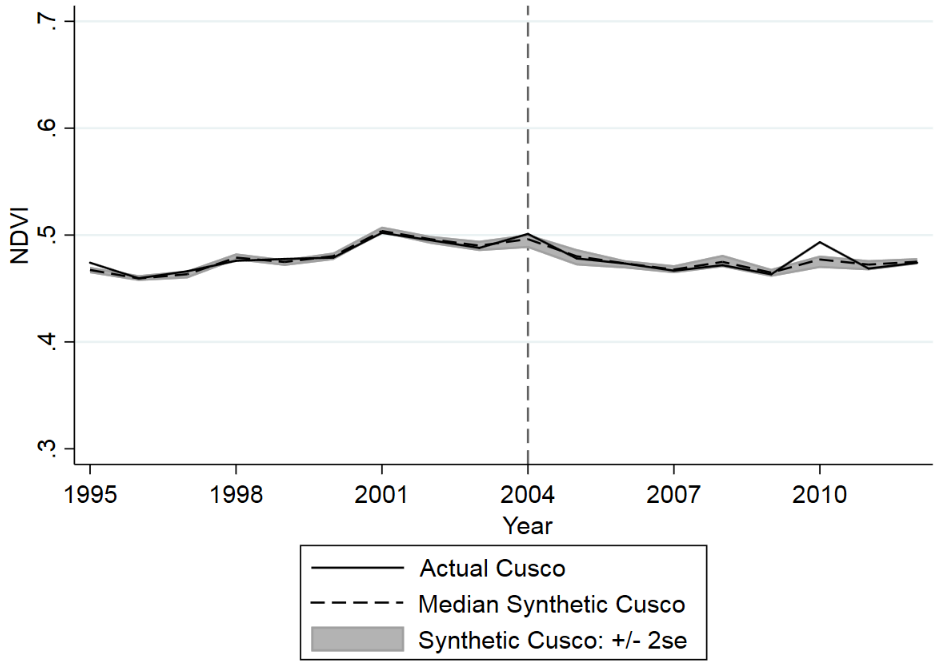


Figure 6. NDVI for Cusco and synthetic Cusco.

In a next step, we examine the post-treatment time period of 2005-2012 to assess the impact that the Camisea Gas Project has had on changes in NDVI levels. It appears that for much of this period, there is no visible effect in deforestation, as measured by the gap between NDVI levels in Cusco and synthetic Cusco. A spike in NDVI levels can be observed in 2010 for Cusco, and this spike is not mirrored by its synthetic counterpart, which suggests that vegetation levels were higher during this year in Cusco.

Table VIII. Gap in NDVI.

Year	**Gap**	**Actual Cusco**	**Synthetic Cusco: 95% Confidence Interval**	
			Low	*High*
2005	-0.002	0.478	0.472	0.487
2006	-0.002	0.473	0.469	0.476
2007	-0.001	0.467	0.464	0.472
2008	-0.004	0.472	0.470	0.481
2009	-0.002	0.463	0.461	0.468
2010	**0.015**	0.493	0.469	0.481
2011	-0.005	0.469	0.467	0.477
2012	0.000	0.474	0.473	0.478

Table VIII displays the gap between NDVI levels in actual and synthetic Cusco and confirms the initial visual impression. Impact remains close to zero for all the years post-treatment except 2010. Impact during these years is not only negligible but also insignificant, as it remains within the estimated 95% confidence interval. For 2010, a difference of 0.015 in NDVI is measured between Cusco and synthetic Cusco, and this positive gap appears significant by exceeding the upper bound of the bootstrapped confidence interval.

This result suggests that the construction and operation of the Camisea gas fields had no sustained, significant impact on deforestation levels in Cusco. Additionally, the influx of royalty transfers, and the capital expenditures thereof, appear to have had no detrimental impact on deforestation. This implies that the Camisea project did not lead to higher deforestation rates, as was feared by environmental organizations (The Economist, 2003) and has repeatedly been claimed since (USAID, 2004; Gamboa et al., 2008; Munilla, 2010). Our finding is in line with the observation made by indigenous environmental monitors of the project that find that in the 11 years since Camisea became operational, there has been no serious impact on the forest (The Economist, 2014). We posit that the set of rigorous environmental safeguards bargained between the GoP, the extraction firm, and the IDB have been successful in preventing adverse ecological effects of the project.

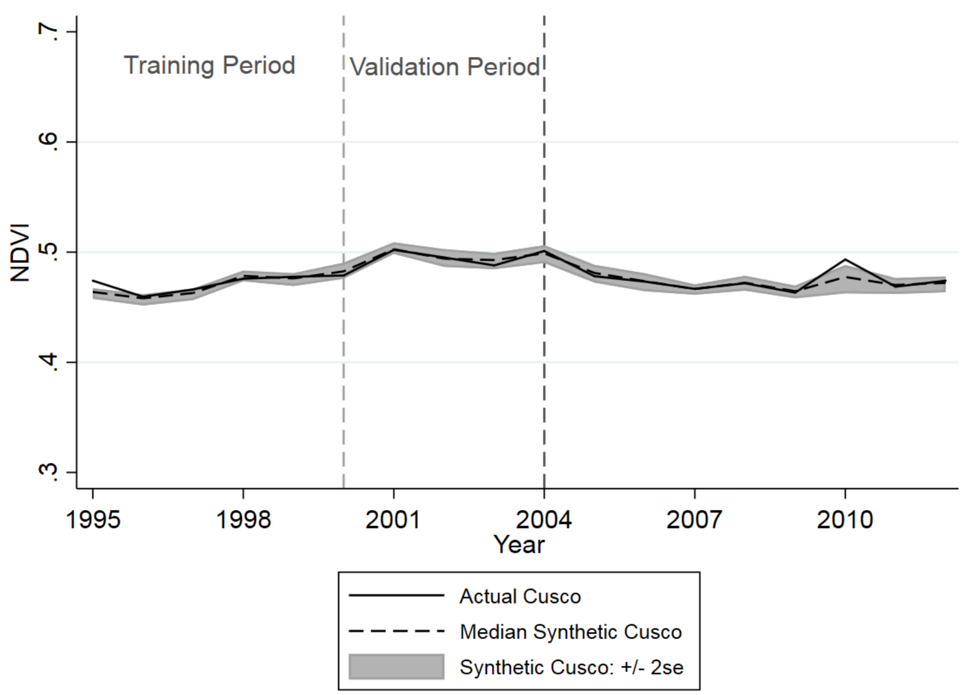


Figure 7. Constructing a synthetic control using cross-validation for NDVI.

To confirm that these results are robust to various potential biases, several robustness and falsification tests are presented below. First, we use the cross-validation test to assess whether the chosen specification of the optimal weights in the V matrix was potentially biased by our subjective assessment of the predictive power of individual covariates included in the specification. The pre-treatment period is divided into a training period from 1995 to 2000, and a validation period of 2001 to 2004. The result of this approach is presented in Figure 7.

Overall, Figure 7 closely mirrors the original specification presented in Figure 5, with a very similar median synthetic control that provides a good fit in the pre-treatment period. The post-treatment trajectory of the synthetic control created with the cross-validation method has a similar trajectory to that of the original specification, though slightly wider confidence bounds indicate that the peak observed in 2010 may be of less significance than inferred from Figure 5.

Table IX. Gap and confidence bounds with cross validation method for NDVI.

Year	**Gap**	**Actual Cusco**	**Synthetic Cusco: 95% Confidence Interval**	
			Low	*High*
2005	0.000	0.478	0.472	0.488
2006	-0.002	0.473	0.465	0.481
2007	0.002	0.467	0.461	0.471
2008	-0.002	0.472	0.465	0.479
2009	-0.002	0.463	0.458	0.470
2010	**0.012**	0.493	0.463	0.488
2011	-0.002	0.469	0.462	0.477
2012	0.001	0.474	0.464	0.478

Table IX presents the estimated impact gap alongside 95 % confidence computed with the cross-validation method for the NDVI. The estimated gap and confidence bounds are very similar to those from the original specification as displayed in Table VIII. The annual gaps are of similar magnitude and significance. Gaps in NDVI between actual and synthetic Cusco are negligible for most of the post-treatment period, though the positive impact measured in 2010 remains significant by exceeding the upper bound of the confidence interval.

Table X. Sensitivity test with bootstrapped confidence bounds for NDVI.

		Without Cajamarca			Without Huancavelica			Without Junín		
			95% CI around Cusco			95% CI around Cusco			95% CI around Cusco	
Year	*Actual Cusco*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*
2005	0.478	-0.002	0.470	0.487	-0.003	0.473	0.488	-0.002	0.470	0.485
2006	0.473	-0.004	0.469	0.477	0.000	0.469	0.476	0.001	0.468	0.475
2007	0.467	0.000	0.464	0.470	-0.001	0.464	0.471	-0.005	0.465	0.473
2008	0.472	-0.002	0.469	0.475	-0.007	0.470	0.481	-0.010	0.468	0.483
2009	0.463	-0.004	0.461	0.469	-0.001	0.461	0.467	-0.002	0.460	0.469
2010	0.493	**0.013**	0.470	0.481	**0.017**	0.469	0.481	**0.023**	0.467	0.476
2011	0.469	-0.004	0.466	0.475	-0.005	0.466	0.476	-0.008	0.466	0.476
2012	0.474	-0.001	0.472	0.478	0.000	0.473	0.478	-0.006	0.472	0.480

		Without Loreto			Without Moquegua			Without Tacna		
			95% CI around Cusco			95% CI around Cusco			95% CI around Cusco	
Year	*Actual Cusco*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*	*Gap*	*Low*	*High*
2005	0.478	-0.005	0.471	0.488	-0.002	0.471	0.487	-0.003	0.472	0.487
2006	0.473	0.002	0.468	0.476	0.000	0.468	0.476	-0.002	0.469	0.476
2007	0.467	0.000	0.464	0.471	-0.003	0.465	0.472	-0.002	0.464	0.471
2008	0.472	-0.002	0.471	0.482	-0.003	0.469	0.481	-0.006	0.470	0.481
2009	0.463	0.001	0.460	0.469	-0.002	0.461	0.469	-0.002	0.461	0.468
2010	0.493	**0.018**	0.469	0.481	**0.016**	0.472	0.481	**0.015**	0.469	0.481
2011	0.469	-0.004	0.469	0.477	-0.002	0.466	0.476	-0.006	0.467	0.476
2012	0.474	-0.002	0.473	0.478	-0.001	0.473	0.478	-0.001	0.473	0.478

Next, we perform a sensitivity tests that sequentially excludes those departments that contributed to the creation of synthetic Cusco. Table X displays the resulting gaps and confidence bounds, where the relevant six donor pool departments were sequentially excluded from the estimation. A visual representation of the sensitivity test can be found in Appendix A. The estimated sensitivity gaps indicate that no one particular donor pool department appears to drive results. Estimated impact gaps remain consistent and of comparable magnitude to that of the original specification, with the average annual gap staying close to zero for all six iterations. The same is true for the bootstrapped confidence bounds. Notably, across all six specifications, the positive peak observed in the year 2010 lies outside of the upper confidence bound and is therefore significant. Though the magnitude of this positive impact varies, it remains relatively small.

These robustness tests confirm what the synthetic control analysis indicated: The impact of the Camisea Gas Project on deforestation was, with exception of 2010, neutral throughout the observed years post-treatment.

6 Conclusion

To our knowledge, this study presents the first rigorous evidence of the economic and environmental effects of a large hydrocarbon project. Concentrating on Peru's largest hydrocarbon project, the Camisea Gas Project, we assess its impact on the producing department of Cusco. Relying on remote-sensing data to measure night-light density as a proxy of economic growth, we apply the synthetic control method to estimate that the economic effect of the Camisea Gas Project accumulates to 27.9% in luminosity, or an annual increase in local GDP of approximately 7.5%. Bootstrapped confidence bounds, and various robustness checks suggest that this positive impact gap is significant for six of the eight years post treatment, 2007 through 2012. Employing a remotely-sensed vegetation index to capture changes in tree cover, we find that the positive economic impact is not associated with an adverse environmental effect: Throughout the post-treatment period, the impact gap remains close to zero and insignificant (except for a positive peak in 2010), suggesting that the Camisea Gas Project and the royalty windfalls thereof did not lead to higher rates of deforestation in the department of Cusco. This is again confirmed by bootstrapped confidence intervals and robustness checks.

To sum up, Camisea gas production generates significant revenues for the department of Cusco. These windfalls have led to meaningful and significant economic growth as captured by nighttime lights. The Camisea gas project and the royalty transfers have not spurred deforestation of the pristine rainforest found in the department. These findings suggest that the Camisea Gas project has contributed to the development of Cusco, thereby avoiding the pitfalls associated with the so-called natural resource course. Specific to the Camisea project, our findings suggest that strict environmental and social safeguards and an explicit commitment to actions geared towards creating long-term benefits for local populations and the environment can lead to sustainable development. The bargaining that took place among the GoP, the extraction firm and the IDB, with the inputs of environmental organizations, as well as the high visibility of the project, and associated reputational risk, provided the impetus for setting rigorous safeguards and dedication to the promotion of sustainable development.

The Camisea project offers important lessons for how hydrocarbon exploitation can be developed and exist within fragile environments and how long-term benefits can be realized. Future research in this vein that assess the economic and ecological impacts of large infrastructure projects would benefit the parties negotiating such projects by providing a careful and complete record of the types of safeguards and other efforts made to avoid negative impacts, as well as the political-economic interactions that are likely driving the evolution of the economic and ecological performance associated with such projects.

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Appendix

A. Additional Tables and Figures

Table AI. Elasticity of GDP with regards to luminosity.[a]

	Log of Cusco GDP p.c.	Log of national GDP p.c.
Log of Cusco luminosity p.c.	**0.17***** (0.02)	
Log of national luminosity p.c.		**0.27***** (0.02)
Constant	**2.87***** (0.15)	**4.39***** (0.03)
Observations	6	21

[a] Difference unequal to zero if p-value significant at the 99 (***), 95 (**), or 90 (*) confidence level. Standard errors reported in parentheses.

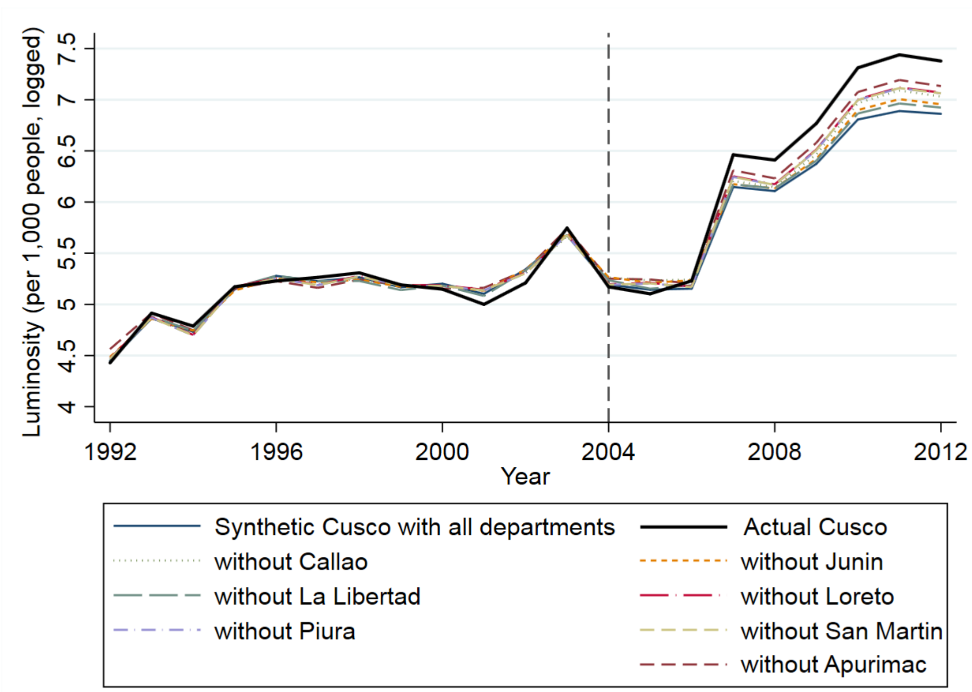


Figure A1. Sensitivity test of sequentially excluding donor pool departments for luminosity.

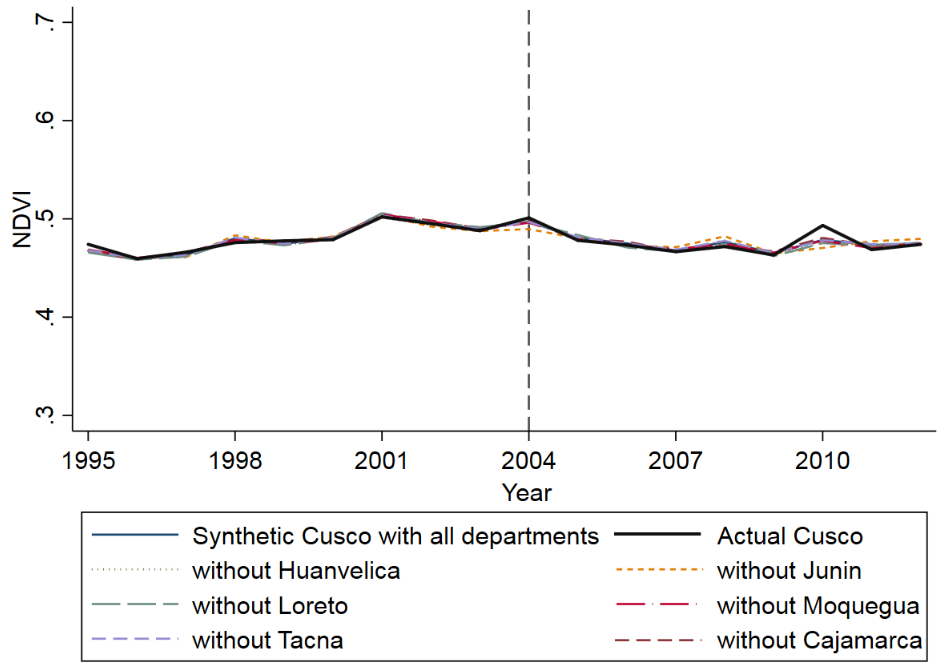


Figure A2. Sensitivity test of sequentially excluding donor pool departments for NDVI.

B. Processing of NDVI Data

This section describes the steps taken to process the raw files provided by NASA to generate yearly measures of the NDVI at department level. All data manipulation was performed in the statistical software R. The following is an example for one year, the same steps are followed for all 21 years in the dataset.

Step 1. Once the data is downloaded from the NASA server, each hdb file is converted into a raster file using the raster package, resulting in more than 7,300 files. These .tif files are then stored in yearly folders to facilitate their further manipulation and analysis. Each raster layer is a matrix with dimensions of 421 rows and 461 columns, for a total of 194,081 cells. The resolution of each image is 0.05 degrees, and its spatial extent is the following: minimum x coordinate -86, maximum x coordinate -63, minimum y coordinate -20, and maximum y coordinate 1. Each file has a file name of the following form: year (4 number digits), month (2 number digits), and day (2 number digits). For instance, January 1st of 1992 is labeled as 1992.01.01.

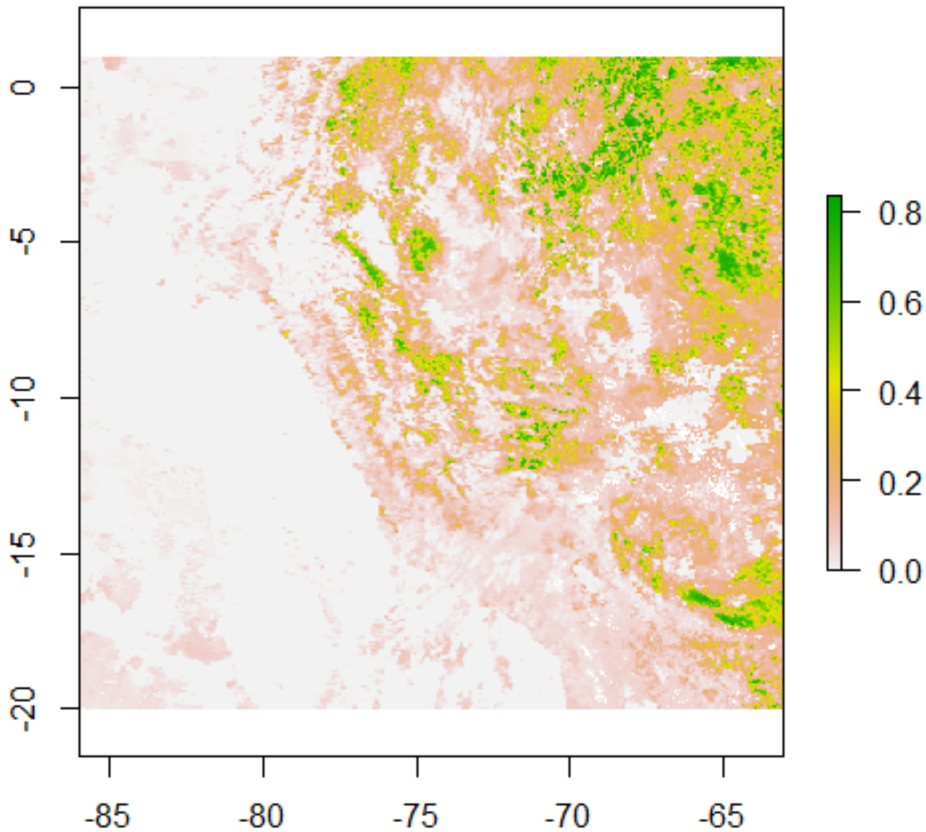


Figure B1. Original NDVI raster from January 1st, 1992.

Step 2. For each year we create a stack of rasters using the stack command. We then truncate the negative values of the cells of each raster layer to zero as they could represent water, snow, ice, dirt, or rock terrain.

Step 3. We create an empty list and store our stack of rasters into that list in matrix form.

Step 4. We create a new list containing 461 empty matrices; each has a dimension of 365 rows and 461 columns. We then use our list from step 3 and, employing a loop, store the first row of matrices from 1 to 365 (or 366 for a leap year), into the first matrix of our new list. This new matrix has dimensions 365 rows by 461 columns. Thus, the first row of this new matrix represents the first row from day 1 of year 1992, the second row the first row of day 2 of year 1992, the third row the first row of day 3 of year 1992, and so forth until we cover all days in 1992. Hence, the second matrix of our new list contains the second row of every day from the same year. Using this method, we fill 421 matrices corresponding to the number of rows of the original raster layer.

Step 5. We add a date column to each of our 421 matrices from step 4. More specifically, a factor variable is added to indicate the month to which each of the rows (days) of the matrix correspond. For instance, in the first matrix the rows from 1 to 31 correspond to January.

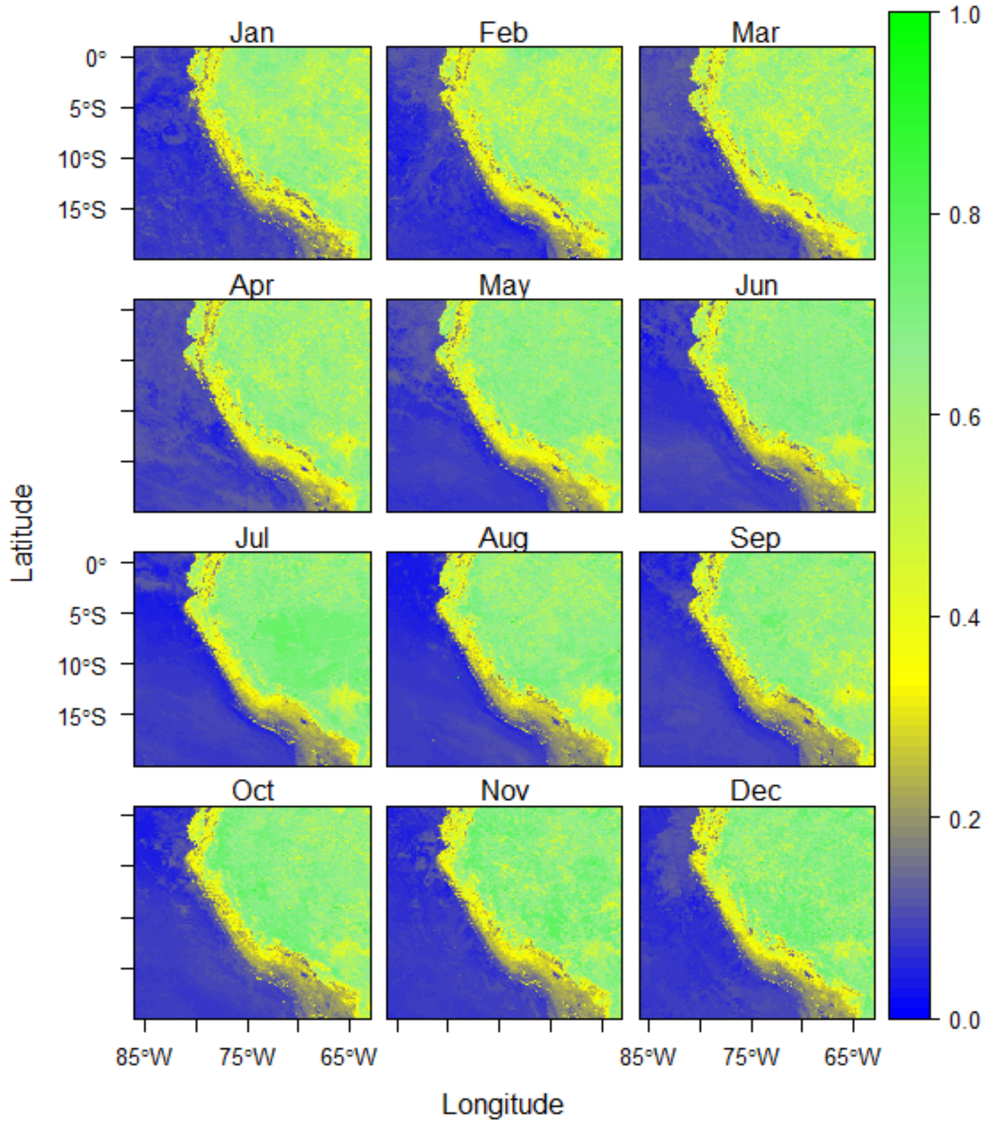


Figure B2. Monthly NDVI in Peru during 1992.

Step 6. We create another empty list with 412 matrices; this time each matrix has dimensions 12 rows by 461 columns. In a next step, we use the group_by and summarize_all functions (using our month variable and estimating the maximum value) and apply them to every matrix from the list in step 5. The corresponding results are stored in our new list. Figure B2 shows the monthly raster files resulting from this step.

Step 7. To facilitate the manipulation of the matrices, we convert the list created in step 6 into a 3-dimensional array with characteristics 421, 461, 12. We eliminate the variables for date and month, and then use the apply function to calculate the mean values for each cell in the array. The result is a single matrix with dimensions 421 rows by 461 columns, which later will represent the raster file for a single year.

Step 8. We convert our single matrix from step 7 back into a raster file. To do so, we again set the coordinate system and the spatial extent from step 1. Figure B3 then presents the resulting raster that contains average NDVI values for an entire year.

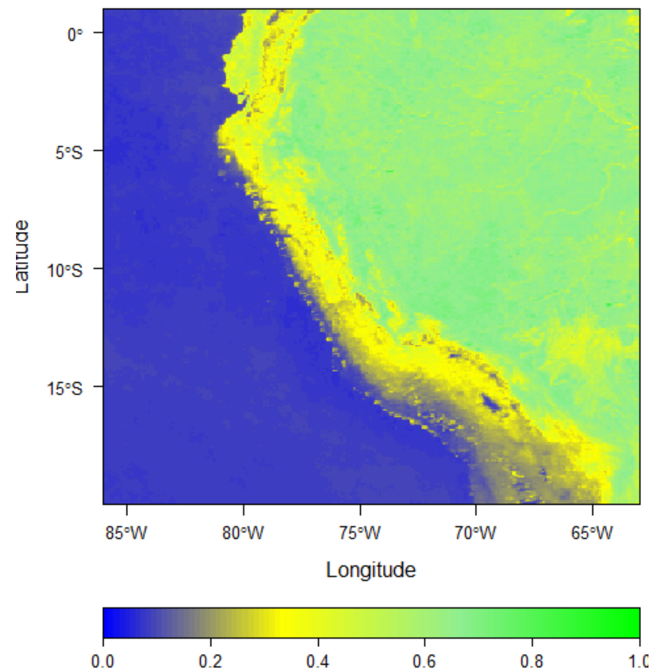


Figure B3. NDVI in Peru for the year.

Step 9. We import the polygon for Peru outlining department borders using the readShapeSpatial function and merge it with our raster file from step 8. Importantly, we employ the extract function from the raster package, using the mean function and setting the options of "weights" and "small" equal to true.[21] Using these settings, the department mean values better

[21] As is explained in the documentation of the Raster Package, when we set the "weights" equal to true we assume that all the cells that overlap with a particular polygon, regardless of whether they do so completely or just in certain parts (in the latter case the cell centroid might not fall into a polygon), should be accounted. On the contrary, if we set the "weights" to false, then only cells whose centroid fall into a polygon should be taken into account. Put differently, the weights indicate which cells (or parts of cells) are going to be considered to extract the values. On the

represent the information for the entire polygon units regardless of their size or location within the polygon. If the units are large, the maximum value might be considerably larger than the mean and could represent an extreme within that polygon, whereas smaller units may receive less weight. The resulting mean department values are depicted in Figure 3, Panel (i) in the main text.

C. Using NDVI to measure deforestation

The Normalized Difference Vegetation Index (NDVI) is an instrument that is commonly used by researchers and analysts to measure how green a patch of land is. The Index uses as a primary element the different colors or wavelengths that are reflected into plants by sunlight. In this regard, the pigment from plant leaves, which is commonly known as chlorophyll, permits plants to absorb visible light, while the cells living in the leaves allow plants to reflect near-infrared light. In other words, vegetation reflects near-infrared light and absorbs red or visible light. Thus, in this manner, the NDVI quantifies vegetation by measuring the difference from the amount of near-infrared light that is reflected by plants and the amount of red light that is absorbed by them. More specifically, the formula to calculate the NDVI is the following:

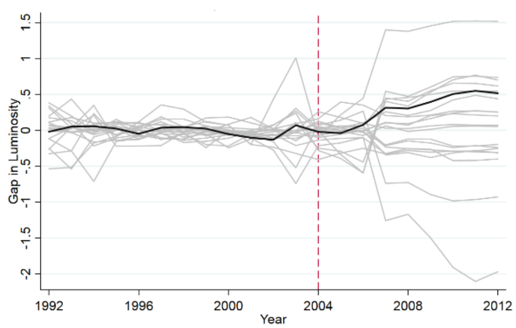
$$\text{NDVI} = \frac{Near\text{−}infrared\ light\ -\ red\ light}{Near\text{−}infrared\ light\ +\ red\ light}$$

Given this formula, the NDVI ranges from -1 to +1. Obviously high levels of near-infrared light combined with low levels of red light will yield a high NDVI, meaning that that area is probably densely green or at least contains a significant portion of green leaves. By the same token, low levels of red light combined with high levels of near-infrared light will yield a low NDVI, meaning that that area has probably very limited vegetation or no vegetation at all (such as water or ice).

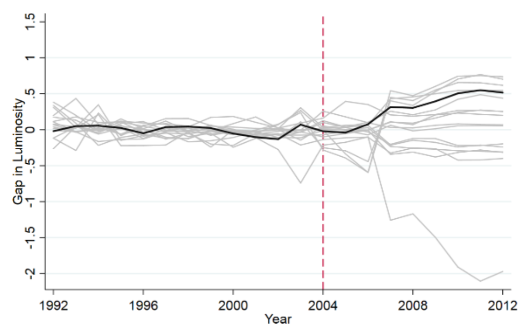
other hand, when we set “small” equal to true, we allow small cells of different shapes to be accounted to extract the values.

D. Additional Robustness Check: Placebo Gaps

As an additional robustness test to the ones already presented in the main body of the study, we assess how often results of the same magnitude can be obtained by fictitious treatment to rule out the possibility that the positive estimate is driven by chance. To this end, departments in the donor pool were assigned a fictitious operation of a gas project similar to that of Camisea in 2004 and the placebo impacts, i.e. the difference between the synthetic and fictitious treatment unit, are graphed for all donor pool departments. In practice, the synthetic control method is iteratively applied to all 22 departments from the donor pool.[22] If this process were to produce consistently positive gaps of similar magnitude for departments that were not the location of this large-scale infrastructure and resource extraction project, this would suggest that the impact results might be related to something other than the Camisea Gas Project.

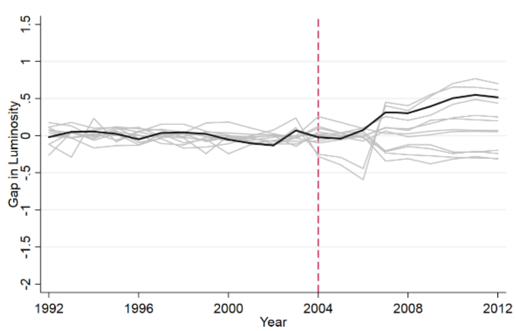


(i) Placebo gaps in all 19 control departments if pre-

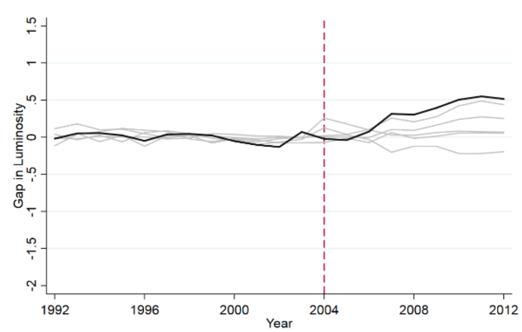


(ii) Placebo gaps in 16 states (excluded

treatment MSPE 20x higher than Cusco's)



(iii) Placebo gaps in 11 states (excluded if pre- if pre-



(iv) Placebo gaps in 5 states (excluded

[22] Cusco is excluded from this iterative process.

treatment MSPE 5x higher than Cusco's) treatment MSPE 2x higher than Cusco's)

Figure D1. Gap in luminosity for Cusco and placebo gaps for states in donor pool.

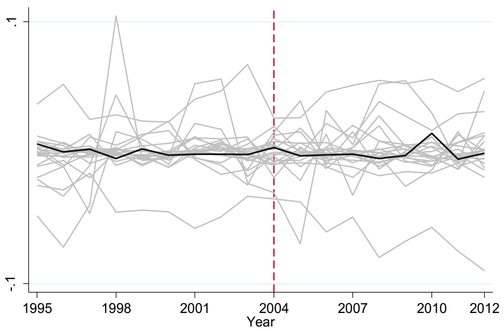
This iterative process for our economic indicator of luminosity renders a distribution of estimated placebo gaps, which are displayed in Panel (i) of Figure D1. The grey lines represent the gaps in luminosity for 19 departments in the donor pool[23], while the bold black line represents the original result obtained for Cusco. In comparison to all other states from the donor pool for which a synthetic counterfactual was created, the estimated gap for Cusco appears relatively strong, but is among several positive impact gaps. However, it is noticeable that the pre-treatment fit is decidedly less accurate for most of these donor departments. While the pre-treatment mean squared prediction error (MSPE) for Cusco has a value of 0.004, the median pre-treatment MSPE for all other donor states is 0.014, which is almost four times larger. This indicates that a convex combination of available donor departments cannot adequately reproduce pre-treatment levels of luminosity for all states in the panel.

Since placebo runs that are unable to create a good fit pre-treatment can provide little reliable information about the significance of any post-treatment gap, Panels (ii) – (iv) present only those placebo runs that provide a reasonably good fit relative to that of the synthetic Cusco version, as measured by the size of their pre-treatment MSPE. Under a restriction of not exceeding Cusco's MSPE by more than 20 times, Panel (ii) displays 16 placebo runs. At this large cutoff point, several other positive impact gaps remain, though they are noticeably much more volatile in the post-treatment period, with a marked negative impact in the first two to three years after Camisea began its operation. In Panel (iii), an additional 5 placebo runs are excluded as they exceed Cusco's MSPE by more than 5 times. The impact for Cusco remains one of few positive post-treatment, while all other placebo gaps indicate negative or neutral impact.

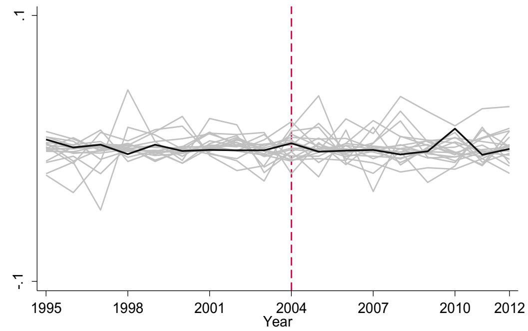
Lastly, Panel (iv) focuses on those departments that can reproduce Cusco's fit as closely as possible, so that six additional departments are excluded because they exceed Cusco's MSPE by more than a factor of two. This confirms that the impact for Cusco stands out as a positive impact that is relatively large in magnitude and is based on a relatively close counterfactual in the pre-treatment period. This is confirmed by a look at the distribution of the ratios of post/pre-treatment MSPEs as another approach to assessing fit, where Cusco exhibits the third highest ratio in comparison to the 22 control departments. The pseudo p-value for the probability of obtaining a post/pre-treatment MSPE ratio as large as Cusco's is therefore 3/22 = 0.136. Though this would not indicate a significant impact of the Camisea Gas Project on economic activity in Cusco on this measure alone, it supports the robust performance of results across all other

[23] Placebo gaps for three control departments could not be constructed from a convex combination of donor states.

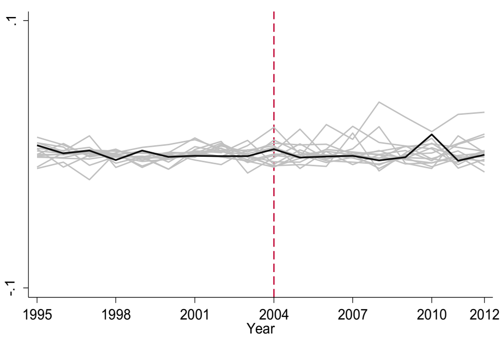
falsification tests and suggests that the analysis can render reliable results about the magnitude and significance of the economic growth effects.



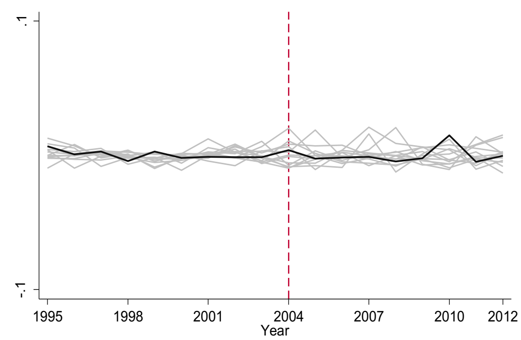
(i) Placebo gaps in all 19 control departments



(ii) Placebo gaps in 16 states (excluded if pre-treatment MSPE 20x higher than Cusco's)



(iii) Placebo gaps in 12 states (excluded if pre-treatment MSPE 5x higher than Cusco's)



(iv) Placebo gaps in 10 states (excluded if pre-treatment MSPE 2x higher than Cusco's)

Figure D2. Gap in NDVI for Cusco and placebo gaps for states in donor pool.

We repeat the same exercise for our environmental indicator. Figure D2 presents the placebo gap results using the NDVI indicator; Panel (i) displays gaps for all 19 control departments.[7] As is visible in this panel, several placebo gaps are quite noisy and unable to provide a good pre-treatment fit, whereas the gap for Cusco remains close to zero during the pre-treatment period. A comparison of the pre-treatment MSPE for Cusco and the average MSPE for all other states confirms this impression: While the pre-treatment MSPE is close to zero for Cusco (9.75×10^{-6}), the average pre-treatment MSPE for the placebo gaps is 0.00004, that is almost 4 times larger.

To again compare Cusco's gap to only those placebo gaps that can provide a comparable pre-treatment fit, panels (ii)-(iv) display only those placebo gaps that do not exceed Cusco's pre-treatment MSPE by more than twenty, five, and two times respectively. As is visible, the distribution of placebo gaps becomes noticeably less noisy, and at the strictest cutoff in panel (iv), a little more than half of all donor placebos remain. Given that the NDVI indicator is less noisy in the pre-treatment period relatively to luminosity, it should not be surprising that more placebo gaps can be created with a relatively accurate pre-treatment counterfactual. Among these ten placebo gaps, the gap for Cusco still remains less volatile in both the pre- and post-treatment period, except for the previously noted peak in 2010. Nevertheless, a look at the distribution of the ratio between post- and pre-treatment MSPEs indicates that Cusco only provides the 8th best fit out of all 22 donor pool departments, resulting in a pseudo p-value of 8/22=0.363. According to this estimate, the results for the environmental effect of the Camisea Gas Project on vegetation would have to be judged as insignificant. Of course, this would be in line with the previously presented robustness checks, which all find that the post-treatment impact on vegetation is neither positive nor negative. In other words, this additional falsification test confirms that the Camisea Gas Project does not appear to have had an adverse effect on deforestation in the Cusco region, suggesting that environmental safeguards may have helped prevent such a negative impact.