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ECON 429

The Ecological and Social Impacts of Revenue Windfalls in the Peruvian Amazon

## I. Introduction

Tropical deforestation is regarded as one of the greatest environmental crises of our time. Tropical forests provide vital support for fundamental biophysical processes such as climate regulation and carbon sequestration (Foley et al., 2007). They also harbor invaluable biodiversity and provide natural resources for millions of people who depend on them. Despite extensive global conservation efforts, the conversion and degradation of tropical forests continue largely unabated. As a result, calls have mounted for rigorous evaluations of the impacts and effectiveness of different conservation approaches. While many empirical evaluations have highlighted a connection between poverty alleviation and deforestation, these tend to focus on programs that pay households directly to protect forests ("Payments for Ecosystem Services"). Far fewer studies have examined the impact of public revenue shocks on deforestation. By leveraging variation in district-level revenues induced by a global oil price shock, this study examines the impact of hydrocarbon revenue windfalls on deforestation and welfare in the Peruvian Amazon.

The focus of my study is Peru's resource canon, a revenue sharing scheme that transfers taxes on extractive industries to local governments based on geographic factors and population needs. While previous research has examined the social and economic impact of Peru's mining canon, few have examined the impacts of the hydrocarbon canon, which is smaller and concentrated in fewer areas. To the best of my knowledge, this is also the first study to examine the impact of revenue windfalls on deforestation in the Peruvian Amazon, the fourth largest country in tropical forest extension on Earth (FAO, 2006).

Theoretically, the effect of revenue windfalls on local forest cover can be positive or negative. More revenue can increase forest cover loss by: (i) facilitating the development of new infrastructure, particularly new roads which increase access to forested land and decreases the cost of agricultural transport. (ii) increasing the value of land for settlement and industry, resulting in forest clearing. On the other hand, revenue windfalls can also reduce forest cover loss by (i) improving social safety nets and infrastructure that enables households to substitute away from forest clearing activities like subsistence agriculture (ii) improving local household and industry access to substitutes for local forest resources (iii) providing access to external output and labor markets, lowering the relative returns to clearing forests for agricultural land.

To test these hypotheses, I combine public finance data, census data, and remote sensing data on deforestation in Peru. I conduct my analysis at the district-level and restrict my study area to all districts in the jungle regions of the Peruvian Amazon. My main estimation strategy combines difference-in-difference estimations with a propensity score matching approach.

My first set of results relate to deforestation outcomes. Using annual district-level deforestation data, I find a non-monotonic relationship between canon revenue and forest loss. For districts below the 50th percentile of the canon distribution, additional revenue has a marginally positive effect on deforestation. Above the 50th percentile, additional revenue has a marginally negative effect on deforestation. At the 50th percentile, a 10-percentile change is expected to decrease deforestation by 35.6 hectares (7.6% decrease at the mean) while a 25-percentile change is expected to decrease deforestation by 215.3 hectares (46% decrease at the mean). These results are robust to propensity score matching, controlling for oil palm expansion as a confounder, and the use of an alternate deforestation dataset.

My second set of results relate to poverty. Using district-level poverty data at three points in time, I find that being in the top quartile of canon revenue distribution significantly reduces poverty rates by 10 percentage points on average. In contrast, I find that canon revenue has no effect on household water access, sanitation access, or electricity access.

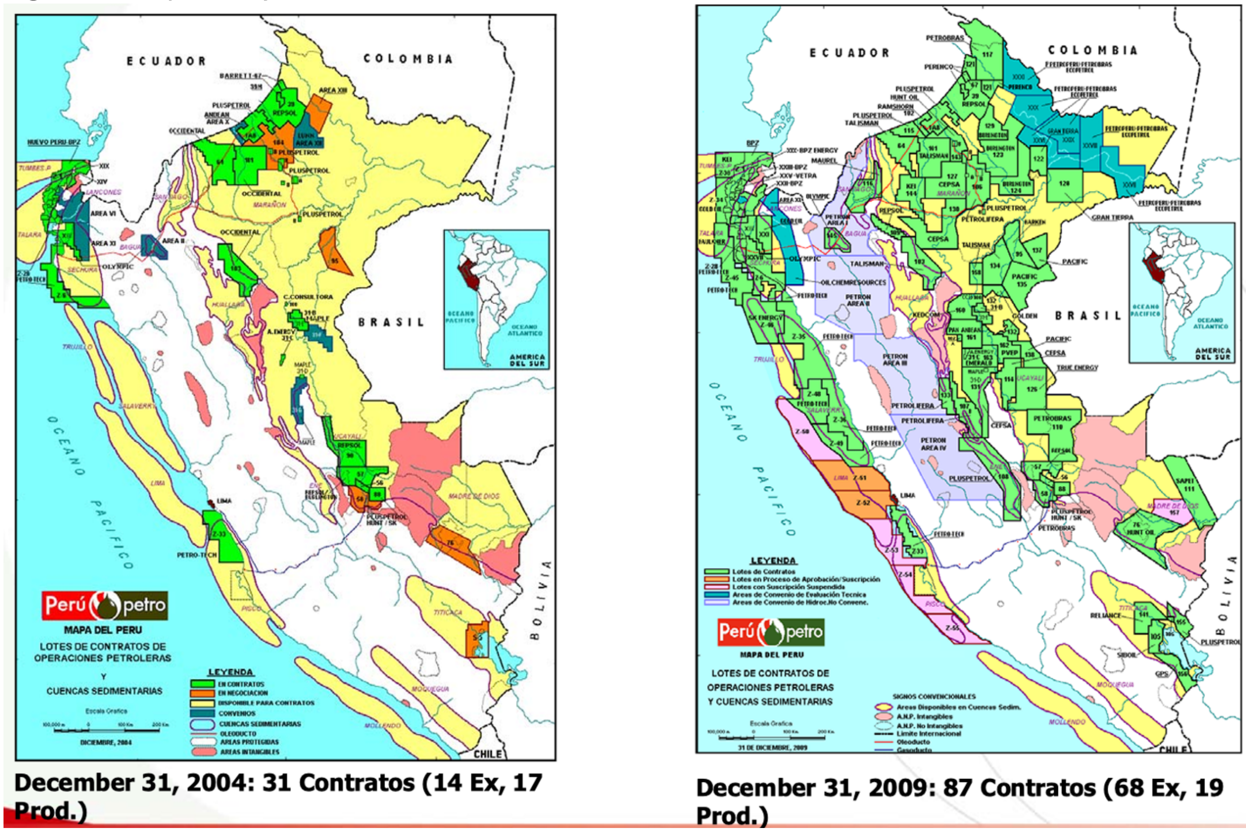
Taken together, these findings suggest that revenue windfalls had positive environmental and social effects on districts receiving high levels of canon transfers. However, districts receiving moderate to low levels of canon did not experience the same returns. This non-monotonic relationship is consistent with prior literature highlighting the existence of non-linear patterns in the relationship between natural resource revenue windfalls and economic and political outcomes (Caselli & Cunningham, 2009; Maldonado, 2022; Agüero et al., 2021).

By leveraging exogenous variation in commodity prices, this study provides evidence that large revenue windfalls have the potential to yield significant benefits for local communities. However, these results do not account for the large negative externalities associated with oil and gas extraction. Rather, they highlight the potential to support conservation efforts by improving public infrastructure and supporting the basic needs of rural communities in tropical forests.

## II. Background and Literature Review

As the second largest piece of the Amazon Basin after Brazil, the Peruvian Amazon is one of the most biodiverse regions on Earth. It is also home to a large indigenous population, including several groups who live in voluntary isolation (Finer & Orta-Martinez, 2010). At the same time, the region continues to be an active and controversial zone of hydrocarbon exploration and production. In Peru, hydrocarbon blocks are delimited by the national government and leased to private companies for exploration and production (Finer & Orta-Martinez, 2010). The first extensive wave of oil exploration in the Western Amazon began in the 1970s. In the mid 2000s, rising global oil prices spurred a second wave of oil and gas exploration. As shown in Figure 1, this period was marked by an unprecedented extension of hydrocarbon concessions. By 2009, hydrocarbon blocks covered vast swaths of the region, though only some areas were successful in production.

*Figure 1. Maps of Hydrocarbon Concessions in 2004 and 2009*




In Peru, taxes on extractive activity are redistributed to local governments through Peru's resource canon. The national government transfers most of the revenue from extractive operations to producing areas, with most revenue accruing to the districts and provinces where the site of production is located. Population levels and basic needs are considered but only within the mineral producing regions. Specifically, the formula allocates 10 percent of the revenue to the producing district(s) and 25 percent to districts in the producing province based on population characteristics (rural share), basic needs, and infrastructure deficits (Aresti, 2016). The remainder is allocated to regional governments.

While Peru's Ministry of Economy and Finance does not disclose the information used to calculate shares for different jurisdictions, the agency does publish data on the annual amount of canon transferred to each district. This data reveals that transfers from the canon surged from early 2000 to 2018 (Figure 2), fueled in large part by an increase in global commodity prices and extractive operations (Aresti, 2016). As shown in Figure 3, the share of total district-level revenue derived from the oil and gas canon ranges significantly across my sample. Among these districts, revenue from the oil and gas canon comprised a substantial share of revenue if districts were exposed to high levels of canon.

*Figure 2. Average District Level Revenue From 1998–2018, By Source.*

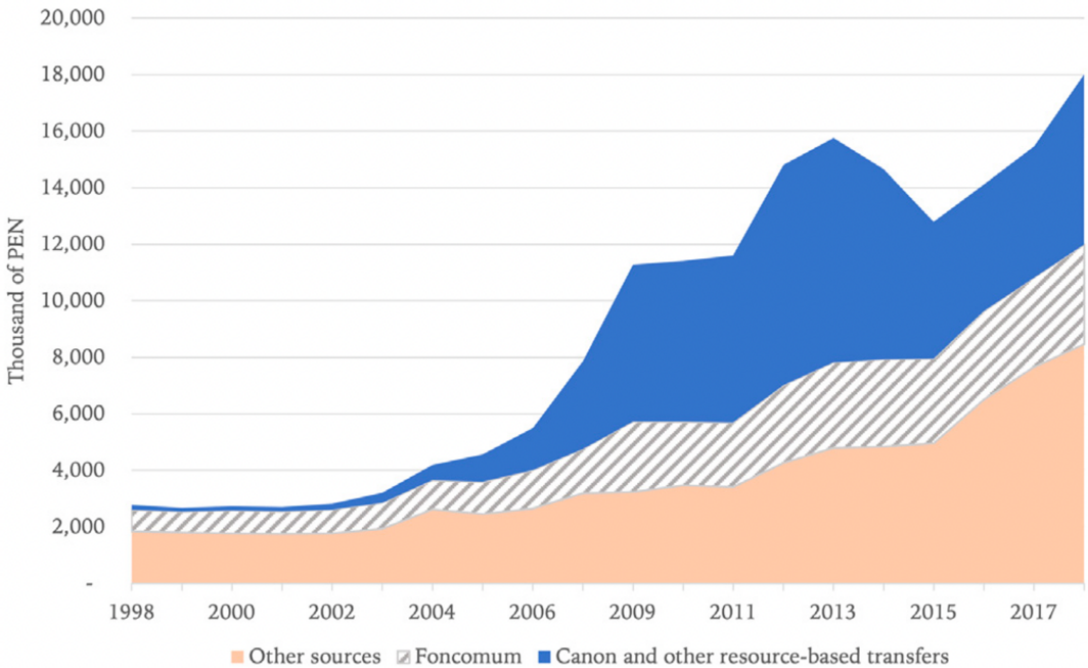
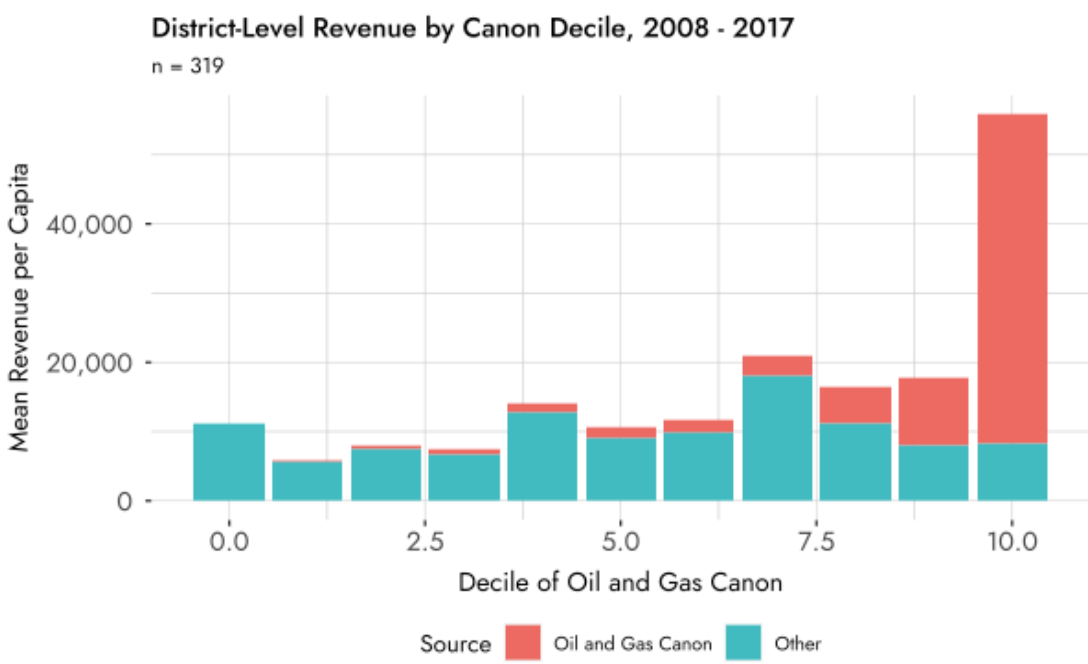
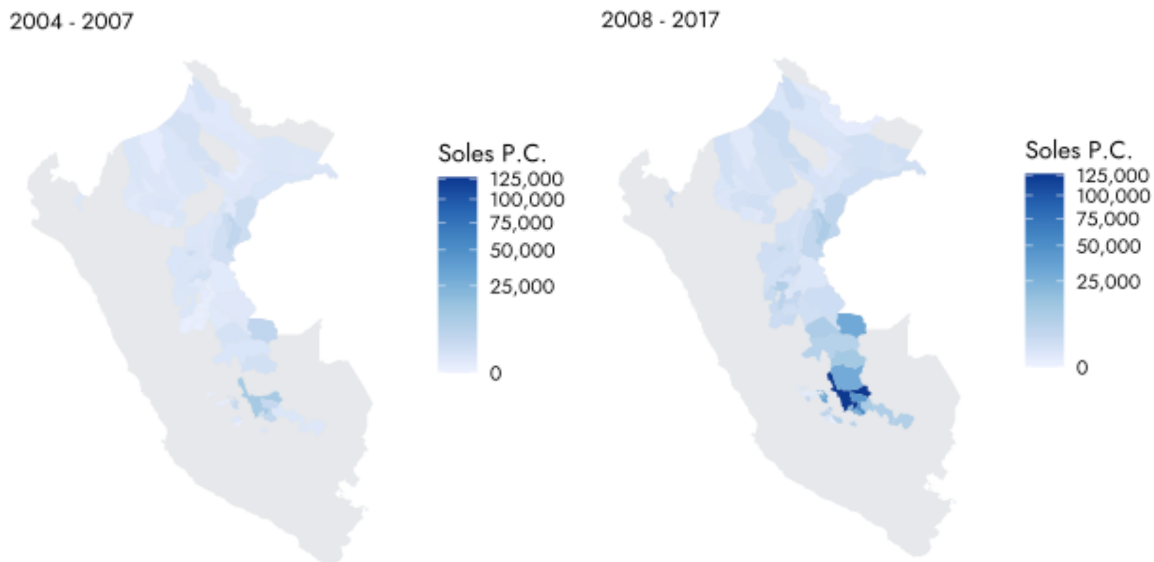



*Figure 3. Average District Level Revenue by Canon Decile (2008 – 2017)*



Across Peru, the canon has contributed to substantial inequality in local budgets. In the case of the late 2000s oil boom, the distribution of canon revenue was highly concentrated in a few regions (See Figure 4). While many districts in producing regions (primarily Ucayali, Cusco, and Loreto) received some level of canon, there were still some that received none at all.

*Figure 4. Distribution of Canon Revenue During Pre-Treatment and Post-Treatment Period*



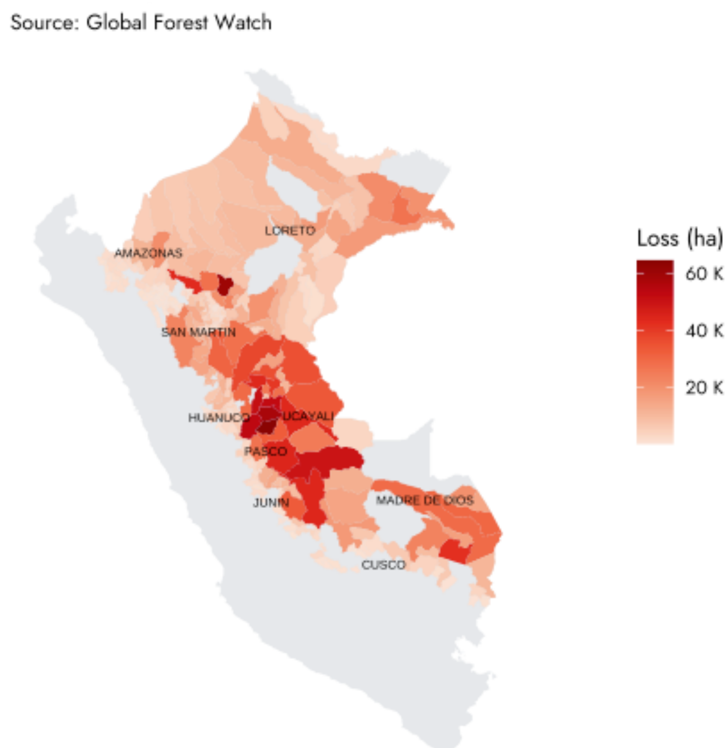

A large body of empirical literature has examined the social and economic impact of revenue windfalls from natural resource extraction. However, many of these studies focus exclusively on cross-sectional data at the national level and are prone to endogeneity concerns. For instance, estimates obtained using this approach may be biased by unobservable characteristics that a priori determine the distribution of extractive activities or revenues in affected areas. Some studies have circumvented these issues by exploiting geographic variation in the abundance of natural resources. For example, Caselli & Michaels (2013) use variation in the location and timing of offshore oil well discoveries to show that oil windfall revenues increase public expenditures but have little impact on public goods provision in Brazilian municipalities.

Several studies have also leveraged temporal variation in global mineral prices to measure the impacts of natural resource production on local communities. For instance, Dube and Vargas (2013) use global commodity prices and local production levels to evaluate the relationship between commodity price shocks and conflict in Columbia. As they point out, exploiting international price changes that are driven by supply shocks originating in other nations helps ensure that this variation is exogenous to their outcome of interest. Using this methodology, they show that rises in oil prices increased both municipal revenue and violence differentially in the oil region. Building on this research, I exploit cross-sectional variation in exposure to Peru's resource canon along with temporal variation induced by a global oil price shock to estimate the impacts of revenue windfalls on local deforestation and welfare outcomes.

While several studies have examined the social and economic impacts of the Peruvian canon, most have focused on the mining canon or the canon more generally. Overall, these studies show mixed results. Some studies find no significant effect of the canon on income, poverty, or inequality, while others highlight a positive or even non-monotonic relationship (Aragón 2013, Loayza and Rigolini 2016, Zambrano et al. 2014, Maldonado and Ardanaz 2023). Moreover, the methods used in these studies vary. Aragón and Winkler (2023) implement several different strategies to mitigate omitted variable bias. Their first method is equivalent to a difference-in-difference model with municipality fixed effects and heterogeneous time trends. Their second strategy utilizes a propensity score matching approach, similar to the methodology used by Ticci and Escobal (2014) and Loayza and Rigolini (2016).

I draw on these methods to examine the impacts of the hydrocarbon canon on deforestation in the Amazon. Unlike Peru's Andes region, where most of the nation's mining activity takes place, the jungle regions of the Peruvian Amazon are geographically suited for oil and gas development. As the fourth largest country in tropical forest extension on Earth (FAO, 2006), the Peruvian Amazon serves as a particularly important site of study. Despite Peru's efforts to adopt international best practices for tropical forest conservation, deforestation has continued to grow, driven primarily by expanding cash crop cultivation (MINAM, 2021). Between 2000 and 2017, the bulk of new forest loss was primarily concentrated in the regions of Ucayali, Huanuco, San Martin, Loreto, and Madre de Dios (Figure 4). In this context, state and international conservation agencies have targeted Indigenous communities with a range of initiatives that aim to help them conserve forests while also pursuing "sustainable" forms of economic development. However, these projects have yielded mixed results in terms of conservation outcomes and have not fundamentally helped rural Indigenous communities meet their basic needs (Angelsen et al., 2018; Brandon, 2001). While many conservation programs offer limited funding to communities for demonstrated reductions in deforestation, they do not allow for significant investments in human capital or infrastructure. At the same time, a primary source of funding that does support rural services are levies from oil, gas, and, in the Andes, mineral extraction. This motivates the question: how have positive revenue shocks from natural resource extraction affected local deforestation outcomes and access to basic services in the Peruvian Amazon?

*Figure 5. District-Level Deforestation in Peru (2001 – 2017)*



## III. Empirical Strategy

### *IIIA. Data*

My study area encompasses all districts in the High Jungle and Low Jungle regions of the Amazon. These regions comprise the largest share of the Amazon and are ecologically distinct from the Andes region, which rests on the Eastern Amazon border. In the deforestation analysis, I restrict my sample to districts where protected area covers less than half of total area, and where forest cover in the year 2000 comprises less than ten percent of total area.

#### *Deforestation*

To measure deforestation between 2001 and 2017, I used the [Global Forest Change] dataset provided by Hansen et al. (2013). This dataset provides a binary measure of annual forest loss per $30m^2$ pixel based on Landsat satellite imagery. Forest loss is calculated relative to baseline forest cover in the year 2000, where the presence of forest area is counted when tree canopy exceeds five meters. My outcome variable is expressed as the amount of forest loss detected in each year within each district.

I verify my estimates using the Geo Bosque dataset published by Peru's Ministry of Agriculture. While both are based on Landsat satellite imagery, the two differ slightly in methodology.

#### *Socioeconomic Outcomes*

The second portion of my analysis examines poverty and public goods provision. This panel dataset draws from three different national censuses (1993, 2007, and 2017). My primary outcomes are measures of poverty and local living standards that could be affected by local governments' policies. These indicators include access to public services (piped water, indoor sewage, and electricity) and the household rate poverty.

#### *Canon Revenue*

Data on annual district-level revenues was obtained from Peru's Ministry of Economy and Finance. All monetary values were deflated to 2010 levels and merged with 2017 National Census data to compute per capita measures revenue.

Exposure to the canon is measured as the total value of canon revenue transferred to a district between 2008-2017. To mitigate the effect of extreme outliers in the data, canon revenue is expressed in terms of percentile ranks. Districts receiving no canon are ranked at the $0^{th}$ percentile.

*Control Variables*

Additional control variables were selected based on a literature review of deforestation drivers in Peru and the other Amazonian countries. These variables are summarized in Table 1 and briefly described below.

I proxy for market access and mobility by calculating the average Euclidean distance from the centroid of each district to its nearest departmental capital. Deforestation can also vary widely across different forest governance (Schleicher et al., 2017). To account for these effects, I calculated the proportion of each district that falls within protected forest areas, indigenous territories, and logging concessions.

Biophysical factors, such as terrain and climate, can affect deforestation through variation in local agricultural suitability and forest growth (Bax & Francesconi, 2018). I therefore control for the average altitude, slope, annual precipitation levels, and baseline temperature of each district. Moreover, I used boundaries on national ecoregions to determine the ecological biome that encompasses the largest area in each district.

All variables were converted into spatially explicit layers and summarized at the district level. As detailed in Table 7, logarithmic and square root transformations were applied to several variables to ensure normality of the residuals. A constant value of 1 to log-transformed variables to avoid zero-values.

*Table 1. Description of variables*

| ***Variable*** | ***Units*** | ***Description*** | ***Transformation*** | ***Source*** | ***Spatial Resolution*** |
|---|---|---|---|---|---|
| *Deforested Area (GFW)* | hectares / year | Annual forest loss detected between 2000 to 2017 | | *Global Forest Watch* | *30m* |
| *Baseline Forest Cover in 2000* | *%* | Percentage of district covered in forested area in 2000 | | *Global Forest Watch* | *30m* |
| *Deforested Area (GB)* | hectares / year | Annual forest loss detected between 2000 to 2017 | | *Geo Bosque* | *30m* |
| *Elevation* | *meters* | Mean elevation | | *Instituto Geográfico Nacional (IGN)* | *1:500 000* |
| *Slope* | *degrees* | Mean slope | | *Instituto Geográfico Nacional (IGN)* | *1:500 000* |
| *Rainfall* | *mm* | Annual precipitation levels | | *CHIRPS* | *0.05°* |
| *Temperature* | °C | Average annual mean temperature recorded between 1981–2020 | | *Huerta et al. 2023* | *0.01°* |
| *Distance to Nearest Capital* | *m* | Distance from district centroid to the nearest department capital | *log* | | |
| *Protected Areas* | *%* | Percentage of district located in a national, regional, or private protected area | *%* | *SERNANP* | |
| *Ecoregions* | *FE* | Categorical variable representing the ecoregion covering the most area in the district | | *MINAM* | |
| *Departments* | *FE* | Categorical variable representing the district department (two | | *Instituto Geográfico Nacional (IGN)* | |

| | | | | | |
|---|---|---|---|---|---|
| | | administrative levels above districts) | | | |
| *Population Density* | *person/ $m^2$* | Population from 2017 census divided by district area | log | [INEI] | |
| *Canon Revenue* | *soles per capita* | Annual per capita revenue from 2004-2017 | | [MEF] | |
| *Poverty Rate* | *%* | Poverty rate reported in 1999, 2007, and 2017 national census | | [INEI] | |
| *Water Access Rate* | *%* | Percentage of households lacking access to a public water network (1993, 2007, 2017) | | [INEI] | |
| *Sanitation Access Rate* | *%* | Percentage of households lacking access to indoor sanitation (1993, 2007, 2017) | | [INEI] | |
| *Electricity Access* | *%* | Percentage of households without electric lighting (1993, 2007, 2017) | | [INEI] | |

*IIIB. Balance Test*

A major threat to validity is that resource-based transfers are not randomly distributed and may be influenced by unobservable characteristics. To address this concern, I conduct a balance test where I distinguish between municipalities with high levels of canon (top 25% of the per capita canon) and low levels of canon (bottom 75%). I use this distinction as the baseline indicator of treatment status.

Table 2 compares key characteristics between these two groups. Overall, districts with high levels of canon tend to be larger, more rural, less accessible by road, and have proportionally more forest cover in the year 2000. In 2007, before the start of the oil boom, these districts also had slightly worse access to public services and marginally higher poverty rates. These differences are likely driven by the canon allocation formula, which prioritizes rural districts with higher demonstrated need.

*Table 2. Balance Test Comparing Districts in the Top Half of the Canon Revenue Distribution to Districts in the Bottom Half*

| | Standardized Mean | | Standardized Difference |
|---|---|---|---|
| | Treated | Control | Treated - Control |
| Resource Canon p.c. (S/) | 1.121 | -0.198 | 1.319 |
| Total Revenue p.c. (S/) | 0.765 | -0.135 | 0.900 |
| Area (km$^2$) | 0.577 | -0.102 | 0.679 |
| Population Density | -0.231 | 0.041 | -0.272 |
| Forest Cover % in 2000 | 0.290 | -0.051 | 0.341 |
| Distance to Nearest Road (km) | 0.291 | -0.051 | 0.342 |
| Rural Share 2007 (%) | 0.361 | -0.064 | 0.425 |
| Poverty 2007 (%) | 0.279 | -0.049 | 0.328 |
| No Water Access 2007 (%) | 0.368 | -0.065 | 0.433 |
| No Sanitation Access 2007 (%) | 0.595 | -0.105 | 0.700 |
| No Electricity 2007 (%) | 0.250 | -0.044 | 0.294 |
| Protected Area (%) | 0.172 | -0.030 | 0.202 |
| Indigenous Territory (%) | 0.608 | -0.107 | 0.715 |
| Logging Concession (%) | 0.355 | -0.063 | 0.418 |
| Average Temperature (C) | 0.274 | -0.048 | 0.322 |
| Annual Rainfall (mm) | 0.352 | -0.062 | 0.414 |
| Elevation (m) | -0.185 | 0.033 | -0.218 |

*IIIC. Empirical Strategy*

My estimation strategy exploits two sources of variation. The first is time variation arising from a shock in global oil prices. The second source of variation is cross-sectional and arises from differences in the share of revenue allocated to a district, as determined by the canon distribution formula. Leveraging the interaction of these two sources of variation, I use a differences-indifferences (DD) approach to compares deforestation levels between districts that are my favored by the canon to districts that are less favored by the canon, before and after the start of the oil boom in 2008.

*Deforestation*

First, I use panel data on annual forest loss between 2001-2017 to estimate the impacts on deforestation at the district-level. My baseline specification is as follows:

$$Deforestation_{it} = \beta_1(f(CP_i) * D_t) + \beta_2(R_{it}) + \beta_3(X_i * Y_t) + FE_i + FE_{dt} + \varepsilon_{it}$$

where $(i, t, d)$ denote respectively district, year, and department. The outcome variable, $Deforestation_{it}$, corresponds to the amount of forest loss (hectares) detected in district $i$ in year $t$. The variable $D_i$ is a binary indicator that equals one in every year starting from 2008, the start of the commodity boom. $f(CP_i)$ is a function of cumulative canon revenue per capita allocated to district $i$ between 2008 and 2017. Due to the substantial variation in canon transfers, $CP_i$ is expressed as a percentile rank. My preferred specification of $f(CP_i)$ is a quadratic function, though I report additional specifications in my results section. $R_{it}$ represents the annual rainfall for each district $i$ in year $t$. $X_i$ is a vector of district-specific time-invariant control variables, including the proportion of baseline forest cover in 2000, distance to the nearest departmental capital, the rural population share in 2007, the poverty rate in 2007, population density, percent of area classified as a protected area, and average slope. Interacting $X_i$ with year dummy variables ($Y_t$) allows these effects to vary flexibly over time. District fixed effects ($FE_i$) are added to control for time invariant factors that vary between districts. Department-year fixed effects ($FE_{st}$) are included to control for any macro level shocks that vary across departments, an administrative unit equivalent to states. $\varepsilon_{it}$ is the error term. A complete list of variables is described below in Table 1.

*Poverty & Public Goods Provision*

The second portion of my analysis estimates the effect of canon revenue on poverty and public goods provision using national census data from the years 1993, 2007, and 2017. My difference-in-differences strategy compares the change in outcomes during the post-oil boom period (2017) relative to the pre-oil boom period (1993 and 2007) between districts that were highly affected by the canon to those that were less affected by the canon. My baseline specification is as follows:

$$y_{it} = \beta_1(f(CP_i) * D_t) + \beta_2(X_i * Y_t) + FE_i + FE_{et} + \varepsilon_{it}$$

where $(i, t, e)$ denote respectively district, year, and ecoregion. The outcome variable, $y_{it}$, corresponds to one of the following four outcome variables: poverty rate (percentage of households in poverty), water access rate (percentage of households without a public water network), sanitation access rate (percentage of households without indoor sanitation services), and electricity access rate (percentage of households without electric lighting). The variable $D_i$ is a binary indicator that equals one in the year 2017, the only year with census data collected after the commodity boom. $f(CP_i)$ is a function of cumulative canon revenue per capita allocated to district $i$ between 2008 and 2017, expressed as a percentile rank. $X_i$ is a vector of district-specific time-invariant control variables, including distance to the nearest departmental capital, the rural population share in 2007, the urban population count in 2007, and the amount of forested area in 2000. Interacting $X_i$ with year dummy variables ($Y_t$) allows these effects to vary flexibly over time. I include district fixed effects ($FE_i$) to control for time invariant factors that differ between districts, and I include ecoregion-year fixed effects ($FE_{et}$) to control for macro level shocks that affect the High Jungle and Low Jungle ecoregions differentially over time. $\varepsilon_{it}$ is the error term.

*Propensity Score Matching*

My second empirical approach uses propensity score matching (PSM) to mitigate the challenges associated with the non-random assignment of canon revenue. The PSM approach constructs an artificial control group that matches each treated unit with a non-treated unit of similar characteristics. In this context, treatment assignment corresponds to being in the top half of the canon revenue distribution.

For the deforestation analysis, matching is done on a set of geographic characteristics, including baseline forest cover, elevation, rainfall, temperature, population density, rural population share, percent of households with piped water in 2007, and distance to the nearest road. This ensures that treated and non-treated districts are comparable based on factors that could influence deforestation rates. For each socioeconomic outcome, matching is based on the outcome measured in 2007, as well as population density, rural share, elevation, and distance to the nearest road.

Figure 8 maps illustrates the weighted sample used for the deforestation analysis after propensity score matching and Figure 9 plots the standardized mean difference of the selected matching covariates. Figure 9 shows that before matching (grey circles), most covariates exhibit significant differences between the treated and control groups. After matching (black circles), the standardized mean differences shrink and cluster around zero, indicating improved balance. By balancing these covariates across treatment and control groups, PSM mitigates the impact of confounding variables, strengthening the robustness of the subsequent analysis.

*Figure 8. Matched Sample for Deforestation Analysis*

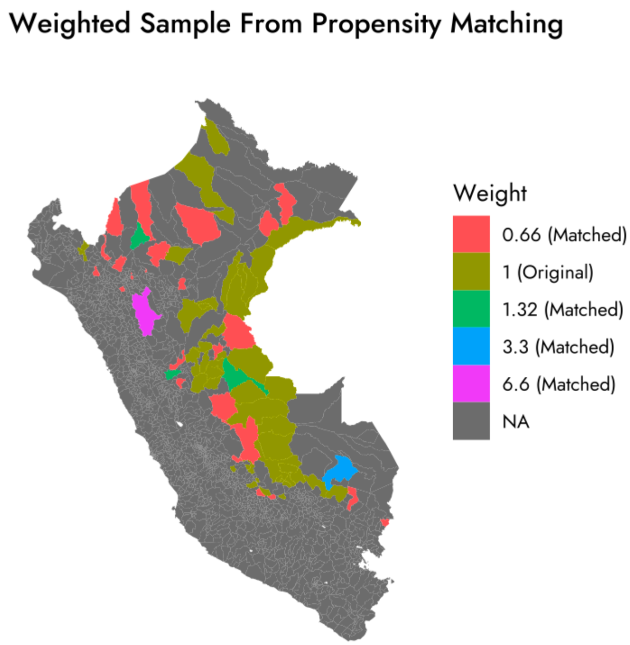
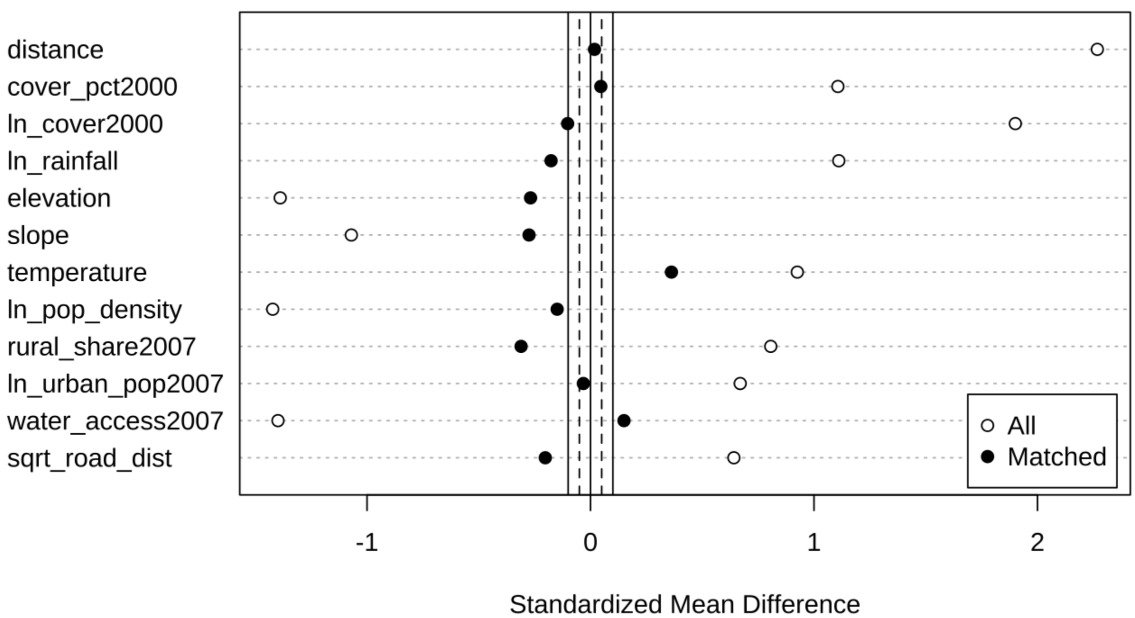



*Figure 9. Standardized Mean Difference of Matching Covariates*



## IV. Results

*IV.A Main Results for Deforestation Outcomes*

Table 4 presents baseline estimates with various specifications of $f(CP_i)$. Column (1) includes a binary treatment indicator that corresponds to being in the top half of the canon distribution, column (2) includes a binary indicator that corresponds to being in the top quarter of the canon distribution, and column (3) includes canon percentile as a continuous measure. The coefficient estimates in all three columns are positive but insignificant.

In column (4), a significant non-linear relationship emerges when canon percentile is expressed as a quadratic polynomial term. The estimated coefficient of the interaction term $(canon\ percentile_i + canon\ percentile_i^2) * D$ reveals the average increase in deforestation arising from a one percentile increase in canon revenue after 2008. The negative coefficient on the quadratic term, $canon\ percentile_i^2 * D,$ indicates that the shape of this regression line resembles a downward facing parabola. According to these estimates, deforestation is expected to increase at an increasing rate for every additional percentile increase from the 0-50$^{th}$ percentile.

For districts below the 50$^{th}$ percentile, every additional percentile increases deforestation at an increasing rate. For every additional percentile after the 50$^{th}$ percentile, canon revenue has an increasingly negative effect on deforestation. At the 50$^{th}$ percentile, a 10-percentile change is expected to decrease deforestation by 35.6 hectares (7.6% decrease at the mean), a 25-percentile change is expected to decrease deforestation by 215.3 hectares (46% decrease at the mean), and a 40-percentile change is expected to decrease deforestation by 546.7 hectares.

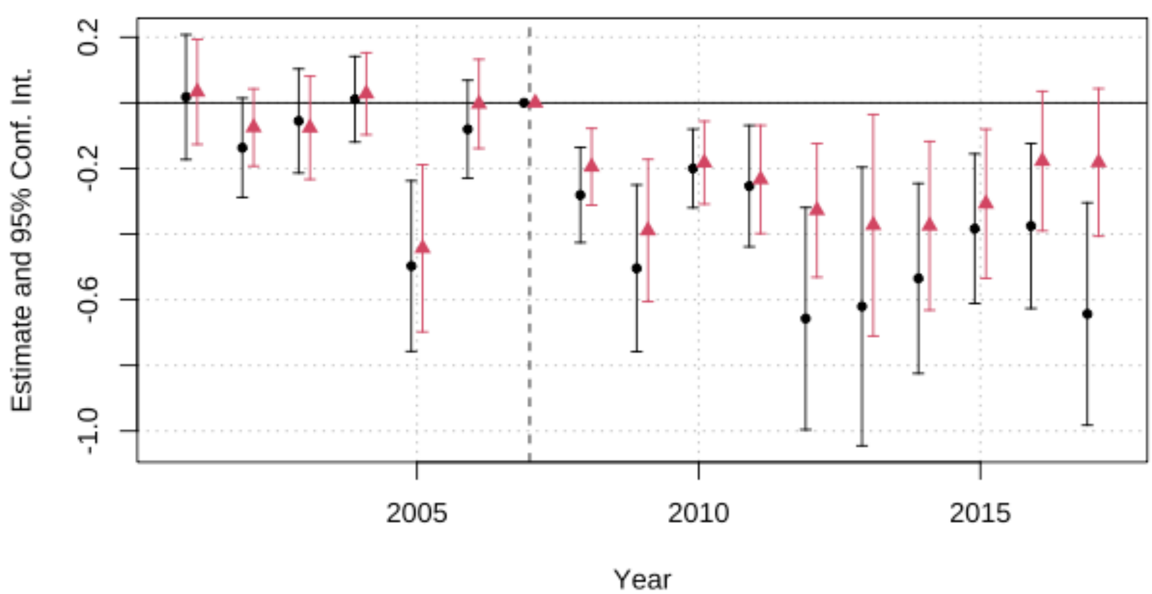
Figure 10 plots the effect of $canon\ percentile_i^2$ on deforestation in each year relative to 2007 levels. Overall, we observe agreement between the two deforestation outcomes derived using the Global Forest Watch and Geo Bosque datasets. The magnitude of the coefficient on $canon\ percentile_i^2$ increases immediately following 2007. Importantly, this plot shows that prior to 2008, district-level deforestation does not appear to depend on levels of canon revenue received. However, a notable exception arises in the year 2005, when deforestation across the entire region spiked. Past research suggests that new logging concessions played a key role in this marked increase (Oliveira et al., 2007).

*Table 4. Baseline estimates of canon revenue on deforestation*

| | Dependent Variable Deforestation | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Canon 25th Percentile × D | 43.8 | | | |
| | (320.5) | | | |
| Canon 50th Percentile × D | | 241.0 | | |
| | | (231.4) | | |
| Canon Percentile × D | | | 6.01 | 34.2*** |
| | | | (3.83) | (10.6) |
| Canon Percentile$^2$ × D | | | | -0.337*** |
| | | | | (0.118) |
| Controls X Year | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | |
| District | Yes | Yes | Yes | Yes |
| Year-Department | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 5,372 | 5,372 | 5,372 | 5,372 |
| $R^2$ | 0.830 | 0.831 | 0.832 | 0.836 |
| Within $R^2$ | 0.131 | 0.136 | 0.141 | 0.164 |

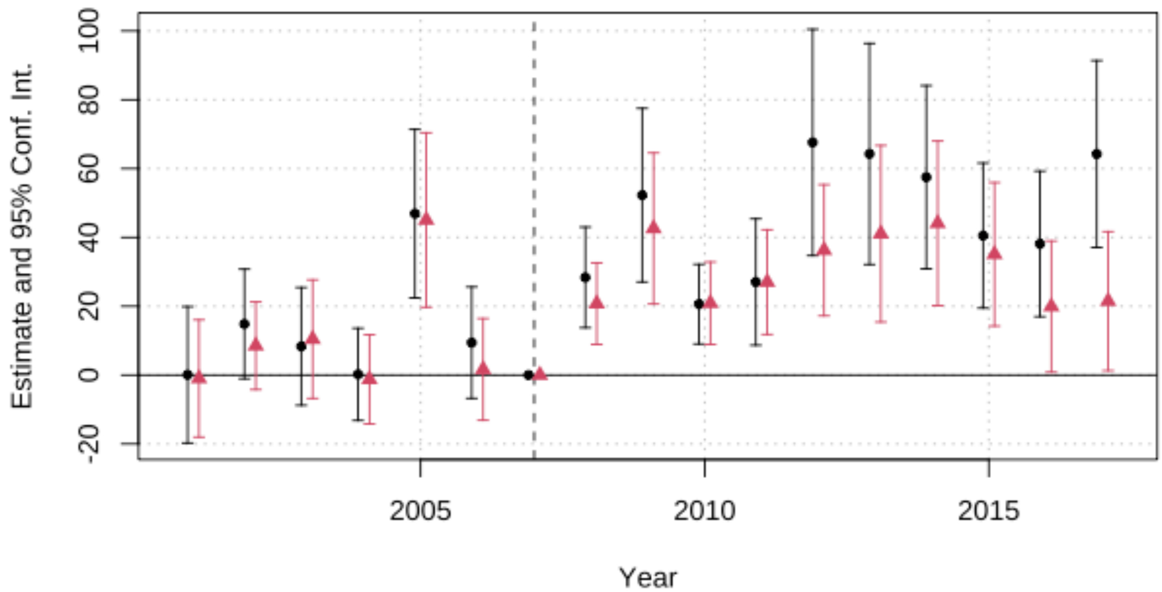
*Clustered (Province) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Figure 10. Effect of $canon\ percentile_i^2$ on deforestation relative to 2007 levels*




*Note: black points correspond to deforestation measured using the Global Forest Change dataset, red corresponds to deforestation measured with the Geo Bosque dataset.*

*Figure 11. Effect of $canon\ percentile_i$ on deforestation relative to 2007 levels*




*Note: black points correspond to deforestation measured using the Global Forest Change dataset, red corresponds to deforestation measured with the Geo Bosque dataset.*

*IV.B Robustness Checks for Deforestation*

The results thus far show that starting after the oil boom in 2008, canon revenue has a significant non-linear effect on deforestation. To check the robustness of the results, I extend the analysis along three dimensions. In Table 5, I present my baseline specification (column 1) alongside three alternative specifications. In column (2), I show that these results are robust to using the alternate Geo Bosque deforestation dataset. Note, this dataset provides more conservative estimates of deforestation relative to the Global Forest Watch dataset. Consequently, the magnitude of the coefficient estimates are smaller.

*Table 5. Baseline estimates of canon revenue on deforestation*

| | Dependent Variable Deforestation | | | | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Canon Percentile$^2$ × D | -0.337*** | -0.198** | -0.323*** | -0.317*** | -0.321*** | -0.294** |
| | (0.118) | (0.089) | (0.111) | (0.108) | (0.109) | (0.116) |
| Canon Percentile × D | 34.2*** | 21.8*** | 33.9*** | 33.7*** | 33.8*** | 30.2** |
| | (10.6) | (7.36) | (9.84) | (9.58) | (9.74) | (11.8) |
| OP Cover × OP Price w/No Lag | | | 0.223** | | | |
| | | | (0.107) | | | |
| OP Cover × OP Price w/1 YR Lag | | | | 0.259*** | | |
| | | | | (0.076) | | |
| OP Cover × OP Price w/2 YR Lag | | | | | 0.223*** | |
| | | | | | (0.051) | |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Alt. Dataset | No | Yes | No | No | No | No |
| Matched Sample | No | No | No | No | No | Yes |
| *Fixed-effects* | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Department | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 5,372 | 5,372 | 5,372 | 5,372 | 5,372 | 1,292 |
| $R^2$ | 0.836 | 0.839 | 0.839 | 0.841 | 0.840 | 0.911 |
| Within $R^2$ | 0.164 | 0.096 | 0.179 | 0.187 | 0.182 | 0.259 |

*Clustered (Province) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Propensity Score Matching*

In my second test, I use propensity score matching to create an artificial sample that is balanced on observable characteristics. This approach requires a binary treatment variable to denote the treatment group. Accordingly, I define treatment as districts in the top two quartiles of the canon distribution.

Column (4) shows that my results are robust to implementing propensity score matching. In fact, the magnitude of the coefficients increase significance after implementing propensity score matching.

*Controlling for Oil Palm Expansion as a Driver of Deforestation*

As one of the largest drivers of deforestation in Peru (Bennett et al., 2018), the expansion of oil palm plantations presents a significant threat to validity. Figures 12 and 13 reveal that rising oil palm prices appear to align with trends in deforestation, raising even greater cause for concern. To ensure that the effect of the oil boom is not confounded by coinciding shocks to the oil palm industry, I compute the level of oil palm cover detected in each district in 2015 based using data from Vijay et al. (2018). In column (3) of Table 5, I interact this variable with annual global palm oil prices. Columns (4) and (5) present the same specification but include a one-year and two-year time lag in global oil palm prices. In all oil palm specifications (columns 3-6), the coefficient on the interaction between oil palm cover*price is positive and significant. However, the coefficients on canon revenue remain highly significant, suggesting that the coinciding expansion of oil palm plantations is not the main driver of this effect.

*Figure 12. Aggregate Deforestation Over Time*

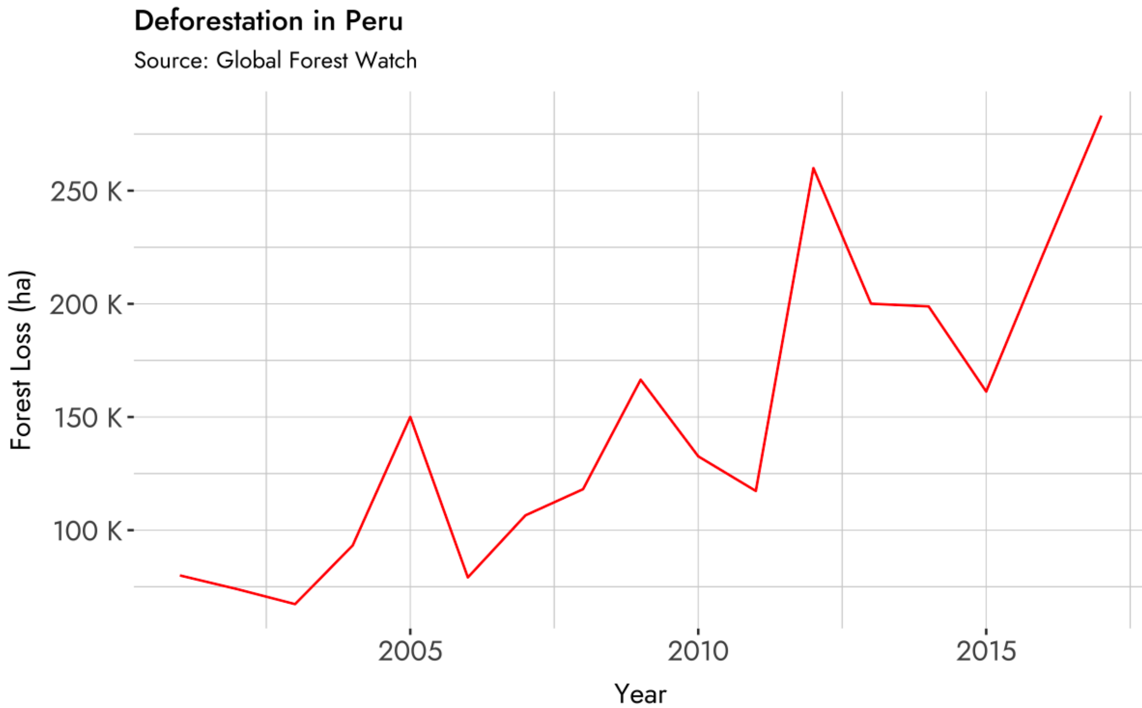
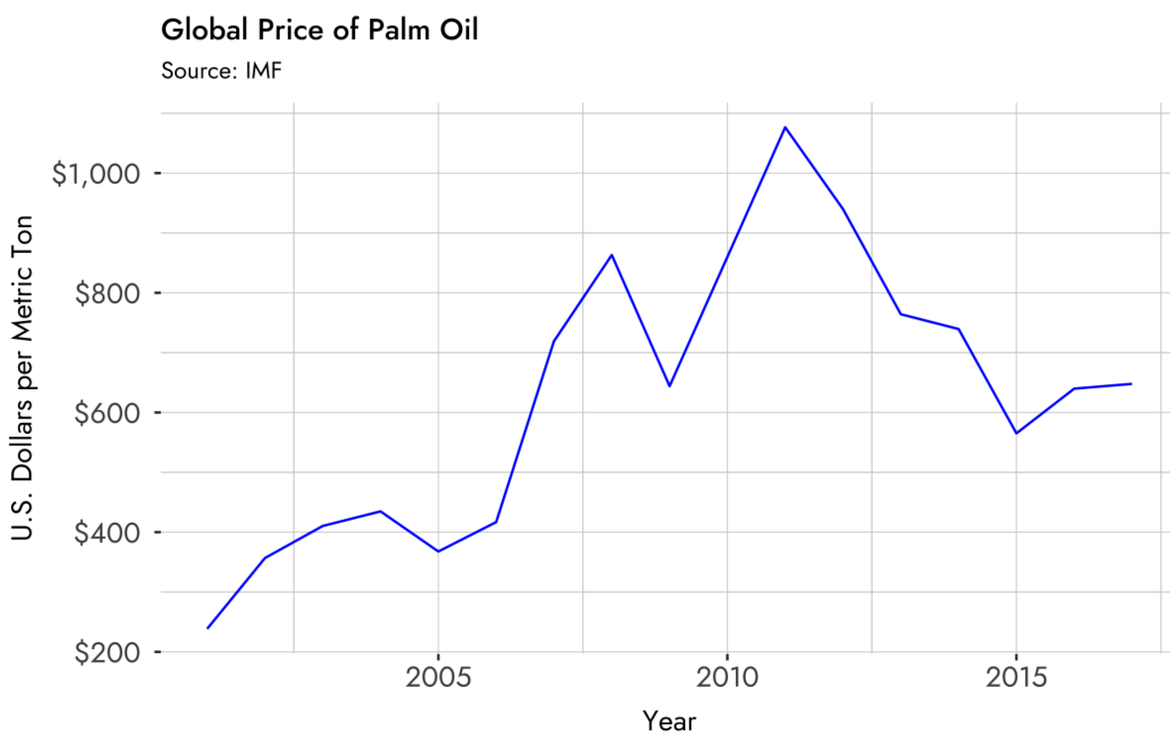



*Figure 13. Global Palm Oil Prices Over Time*



*Spatial Autocorrelation*

Deforestation often exhibits strong spatial dependence due to the nature of the phenomena involved. Geographical proximity plays a significant role in influencing deforestation patterns because changes in one area can have spillover effects on neighboring regions through ecological, economic, and policy channels. If spatial correlations are present in the data, traditional standard errors falsely assume observations are independent, leading to biased and inconsistent estimates. Conley standard errors can correct for these issues by adjusting for spatial autocorrelation within a specified distance. This makes Conley standard error more flexible than other methods that assume specific forms of spatial dependence.

To account for potential spatial autocorrelation, I test my baseline specification using Conley standard errors of varying bandwidths. As shown in Table 6, my results are robust to using bandwidth lengths up to 500km.

*Table 6. Baseline deforestation estimates with Conley standard errors*

| | Dependent Variable Deforestation | | | | | | |
|---|---|---|---|---|---|---|---|
| Model: | (10km) | (20km) | (50km) | (100km) | (200km) | (300km) | (500km) |
| *Variables* | | | | | | | |
| Canon Percentile$^2$ × D | -0.337*** | -0.337*** | -0.337*** | -0.337*** | -0.337*** | -0.337*** | -0.337*** |
| | (0.092) | (0.096) | (0.086) | (0.081) | (0.098) | (0.089) | (0.072) |
| Canon Percentile × D | 34.2*** | 34.2*** | 34.2*** | 34.2*** | 34.2*** | 34.2*** | 34.2*** |
| | (7.76) | (8.90) | (8.98) | (9.85) | (10.4) | (8.56) | (5.50) |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Excludes Cusco | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Department | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 5,372 | 5,372 | 5,372 | 5,372 | 5,372 | 5,372 | 5,372 |
| $R^2$ | 0.836 | 0.836 | 0.836 | 0.836 | 0.836 | 0.836 | 0.836 |
| Within $R^2$ | 0.164 | 0.164 | 0.164 | 0.164 | 0.164 | 0.164 | 0.164 |

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*IV.C Discussion of Deforestation Results*

Overall, I find a non-linear relationship between canon revenue and deforestation. These results are robust to accounting for the confounding effects of oil palm expansion, implementing propensity score matching, and using Conley standard errors to account for spatial autocorrelation.

According to my baseline specification (reported in column 1 of Table 5), additional exposure to the canon has an increasingly positive effect on deforestation for districts below the 50$^{th}$ percentile. Between 2008 and 2017, districts at the 50$^{th}$ percentile received approximately 16 percent of total revenue from the oil and gas canon, compared to 56 percent for districts at the 90$^{th}$ percentile. Thus, districts in the bottom half of the distribution benefit only moderately from the canon. The positive deforestation effect observed for these districts is likely related to the canon distribution formula, which considers various indicators of need in addition to geographic proximity. Districts below the 50$^{th}$ percentile are most likely not producing districts[1]. Rather, these districts likely receive canon revenue because they are a) located in the same province as a producing district and b) demonstrate some level of need. Past research indicates that non-producing recipients of the canon tend to be poorer and more rural relative to the average potential beneficiary (Loayza & Rigolini, 2016). Hence, canon may increase deforestation in these districts because they are poorer to begin with and do not enjoy the full benefits of new development, such as the creation of new jobs and robust public spending.

This finding is also in line with prior literature suggesting a non-monotonic relationship between revenue windfalls and public expenditure. Maldonado and Ardanaz (2023) show that the change in public expenditures induced by Peru's mining canon varies according to the level of transfers received. They find that "Transport" expenditures category experienced the most dramatic increase as a result of the revenue windfalls. However, resource-rich districts spent significantly less on transportation than the average district, where "Transport" expenditures increased by 250 soles for every 1000 soles of canon transfers (Maldonado & Ardanaz, 2023). Given that road construction is widely considered to be one of the largest drivers of deforestation in the Peruvian Amazon (Bax et al., 2016), this finding is consistent with a positive deforestation effect of additional canon for districts receiving low/moderate levels of canon.

In contrast, districts receiving high levels of canon are most likely to be producing districts. This means that benefits accrue to these districts because they are geographically suitable for production. These districts experience the opposite effect. That is, more revenue is expected to have an increasingly large negative effect on deforestation. There are many reasons why this may be the case. First, a substantial influx of new revenue may allow districts to substitute away land-intensive agricultural activity. In producing districts, the

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[1] Producing districts house the site of oil and gas production. These districts are awarded the most revenue by the canon distribution formula.

expansion of oil and gas operations can increase employment and demands for local goods and services, which can help diversify income sources away from the agricultural sector. Revenue windfalls can also be used to finance health and educational services, infrastructure, and other public goods that increase physical and human capital accumulation. Oil and gas development can also affect the agricultural sector through crowding out. For instance, hydrocarbon extraction often relies on intensive water use, requires extensive land area, and can result in major environmental externalities (Finer & Orta-Martinez, 2010).

*IV.D Results for Socioeconomic Outcomes*

In Tables 7-10, I report estimates with canon revenue expressed in various forms. Table 7 and Table 8 reports canon as a continuous measure of treatment, expressed as quartiles and deciles of canon, respectively. Table 9 and Table 10 reports canon as a binary measure of treatment, expressed as being in the top quartile or top two quartiles, respectively.

In all specifications, the significant negative coefficient in column (1) reveals that canon reduces poverty. The magnitudes of the coefficients are relatively similar across these different specifications. However, column (2) shows that this effect is only robust to propensity score matching (remains significant at the 5 percent level) when treatment is defined as being in the top quartile. Specifically, this specification indicates that being in the top quartile decreases poverty rates by 10 percentage points on average. At the mean poverty rate of 44 percent, this effect translates into a substantial 22.8 percent reduction.

Next, I report estimates on measures of public goods provision. Across all four specifications, insignificant coefficients in columns (3) – (8) reveal that canon revenue has no effect on household water access, sanitation access, or electricity access.

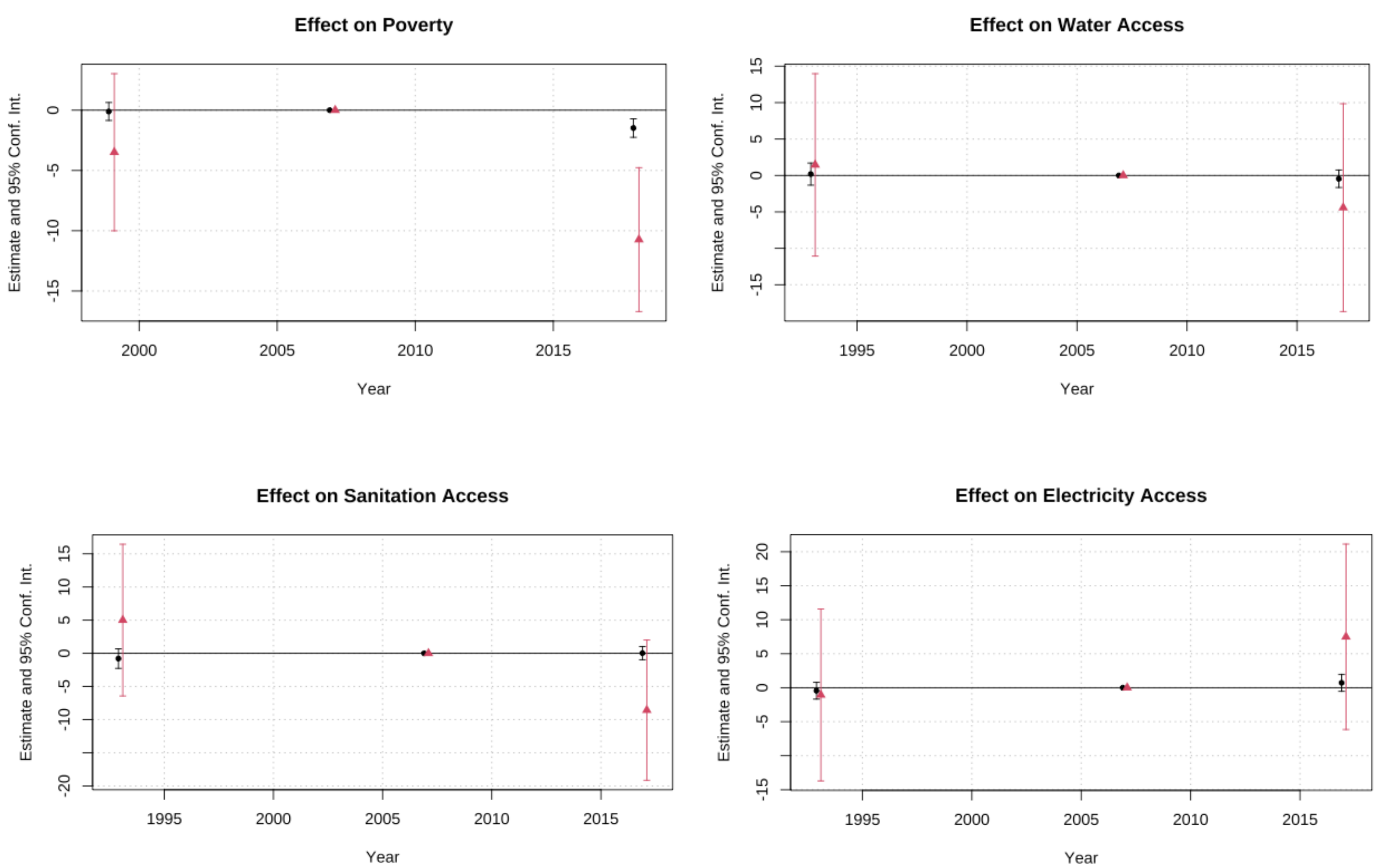
For all outcomes, we do not observe any clear trends of the estimated interaction effects prior to the oil boom (Figures 14a-d). For the poverty outcome, the magnitude of the coefficient on $Top\ Quartile$ sharply increases in 2017, the only year measuring post-boom outcomes.

This negative impact of canon on poverty rates is consistent with research by Loayza and Rigolini (2016), who study the impacts of Peru's mining canon. Specifically, they find significant reductions in poverty in districts where mining production takes place. In other words, the benefits of mining activity are localized to producing districts, who receive the bulk of profits from mining activity.

This lack of impact on public goods and services is consistent with prior evidence by (Aragón & Winkler, 2023), Caselli & Michaels (2009), and Ticci and Escobal (2015). In their evaluation Brazil municipalities, Casseli and Michaels (2010) find that revenue windfalls from offshore oil wells translate into increases in public expenditure but have insignificant impacts on public goods and services. In studying the long-term impacts of the overall resource canon in Peru, (Aragón & Winkler, 2023) find no significant effects on access to public services or poverty levels. Similarly, Ticci and Escobal (2015) find that new mining operations in Peru did not improve access to public services between 1993 and 2007.

The lack of impact on public goods and services can be attributed to several possible explanations. First, it's possible that improvements to water, sanitation, and electricity infrastructure are hindered by the geography of the Amazon. As discussed earlier, districts affected by the canon tend to be more remote, less dense, and further from roads. Thus, the cost of upgrading water, sanitation, and electricity infrastructure may be significantly higher in these districts. It's also possible that local governments prefer to allocate revenue windfalls on projects that are not reflected in these outcomes. For instance, Aragón & Winkler (2023) find positive effects of the overall resource canon on transport infrastructure projects and municipal resources, such as personnel and vehicles. Furthermore, it's possible local governments lack the technical capacity to use the canon effectively. For instance, Loayza et al. (2014) and Hoyos (2019) find suggestive evidence that lack of technical capacities was an important constraint for local governments to use their budget on investment projects effectively.

*Figures 14 a-d.*




Note: red points correspond to the coefficient on top quartile*D, black points correspond to the coefficient on canon decile*D.

*Table 7. Effect of canon quartile on poverty and public goods*

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Poverty Rate | | No Water Acc. % | | No Sanitation Acc. % | | No Electricity % | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| Canon Quartile × D | -3.418*** | -3.653 | -1.023 | -0.466 | -0.598 | -0.029 | 1.621 | 3.930* |
| | (0.986) | (2.259) | (1.571) | (2.072) | (1.149) | (2.202) | (1.512) | (2.254) |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Matched Sample | No | Yes | No | Yes | No | Yes | No | Yes |
| *Fixed-effects* | | | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Ecoregion | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 885 | 255 | 877 | 276 | 877 | 246 | 877 | 252 |
| $R^2$ | 0.87002 | 0.89295 | 0.80998 | 0.81841 | 0.88415 | 0.87338 | 0.87090 | 0.85660 |
| Within $R^2$ | 0.17507 | 0.38257 | 0.14237 | 0.25778 | 0.23880 | 0.19517 | 0.14289 | 0.24471 |

*Clustered (District) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Table 8. Effect of canon decile on poverty and public goods*

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Poverty Rate | | No Water Acc. % | | No Sanitation Acc. % | | No Electricity % | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| Canon Decile × D | -1.518*** | -1.818* | -0.398 | -0.158 | -0.171 | -0.102 | 0.604 | 1.455 |
| | (0.423) | (0.971) | (0.649) | (0.879) | (0.486) | (0.913) | (0.657) | (1.017) |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Matched Sample | No | Yes | No | Yes | No | Yes | No | Yes |
| *Fixed-effects* | | | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Ecoregion | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 885 | 255 | 877 | 276 | 877 | 246 | 877 | 252 |
| $R^2$ | 0.87019 | 0.89405 | 0.80995 | 0.81837 | 0.88411 | 0.87339 | 0.87080 | 0.85515 |
| Within $R^2$ | 0.17617 | 0.38889 | 0.14226 | 0.25764 | 0.23857 | 0.19527 | 0.14224 | 0.23707 |

*Clustered (District) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Table 9. Effect of being in the top quartile on poverty and public goods*

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Poverty Rate | | No Water Acc. % | | No Sanitation Acc. % | | No Electricity % | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| D × Canon 25th Percentile | -10.982*** | -9.921** | -4.303 | -4.423 | -8.180 | -6.298 | 7.405 | 11.637 |
| | (3.174) | (4.295) | (7.453) | (8.061) | (5.423) | (7.358) | (7.097) | (7.624) |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Matched Sample | No | Yes | No | Yes | No | Yes | No | Yes |
| *Fixed-effects* | | | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Ecoregion | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 885 | 255 | 877 | 276 | 877 | 246 | 877 | 252 |
| $R^2$ | 0.86911 | 0.89180 | 0.80998 | 0.81894 | 0.88474 | 0.87441 | 0.87096 | 0.85550 |
| Within $R^2$ | 0.16932 | 0.37590 | 0.14236 | 0.25997 | 0.24267 | 0.20176 | 0.14328 | 0.23889 |

*Clustered (District) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Table 10. Effect of being in the top two quartiles on poverty and public goods*

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Poverty Rate | | No Water Acc. % | | No Sanitation Acc. % | | No Electricity % | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| D × Canon 50th Percentile | -6.138** | -3.620 | -4.614 | -6.234 | -0.469 | -0.250 | 6.130 | 7.790 |
| | (2.534) | (4.146) | (3.978) | (4.577) | (3.364) | (5.290) | (4.415) | (5.471) |
| Controls X Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Matched Sample | No | Yes | No | Yes | No | Yes | No | Yes |
| *Fixed-effects* | | | | | | | | |
| District | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Ecoregion | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 885 | 255 | 877 | 276 | 877 | 246 | 877 | 252 |
| $R^2$ | 0.86864 | 0.88934 | 0.81016 | 0.82039 | 0.88409 | 0.87338 | 0.87115 | 0.85444 |
| Within $R^2$ | 0.16628 | 0.36175 | 0.14318 | 0.26590 | 0.23842 | 0.19519 | 0.14455 | 0.23330 |

*Clustered (District) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## V. Conclusion

This study exploits variation in hydrocarbon production and global oil prices to examine the impact of revenue windfalls on deforestation and welfare in the Peruvian Amazon. My results reveal a non-monotonic relationship between deforestation and revenues transferred through the "canon," Peru's national revenue-sharing scheme. Specifically, I find that additional canon increases deforestation for districts in the bottom half of the canon distribution but decreases deforestation for districts in the top half. Furthermore, I find that high levels of canon revenue (being in the top quartile) significantly reduces poverty (10 pp on average) but has no effect on access to basic goods and services.

These findings have significant policy implications. First, they show that moderately affected communities are less likely to realize the potential benefits of positive revenue shocks. Thus, improving the technical capacity of local governments to manage revenue windfalls and prioritize human capital investments may enhance the overall effectiveness of revenue-sharing schemes. Second, by leveraging exogenous variation in commodity prices, this study provides evidence that large revenue windfalls have the potential to yield significant benefits for local communities. However, these findings do not account for the numerous negative externalities associated with oil and gas extraction. Moreover, by focusing exclusively on positive revenue shocks from natural resource extraction, this study fails to account for the costs associated with economic reliance on volatile commodity markets. In this context, this research highlights the potential for conservation programs to improve deforestation outcomes by improving investments in local communities, such as access to basic public services.

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