# The long-term impact of a resource-based fiscal windfall: evidence from the Peruvian canon

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**Abstract**

This paper examines the long-term impact of the canon, a resource-based transfer, on local living conditions in Peruvian municipalities. We use the most recent data and several identification strategies with cross-section and panel data. We find no evidence of significant improvements in access to public services, poverty, or inequality. This negligible impact occurs, even though we do observe sizable increases in municipalities' revenue, personnel, and equipment. We only observe some suggestive, albeit weak, evidence of increased infrastructure projects in local areas, such as the construction and repair of urban roads.

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# 1 Introduction

When evaluating the effects of mining and other extractive industries, an important consideration is whether they can benefit local communities. One possible transmission channel is through a monetary windfall. Resources from revenue-sharing agreements, royalties, or local taxes can allow local governments or other organizations to offer public services, enhance local infrastructure, and promote local economic activity.

However, our understanding of the effectiveness of this mechanism is still limited, especially in less developed countries. Empirical findings on this matter are mixed. While some studies demonstrate positive impacts resulting from a revenue windfall, others indicate negligible or even negative effects (Aragón and Rud, 2013, Brollo et al., 2013, Busse and Gröning, 2013, Caselli and Michaels, 2013, Fleming et al., 2015, Paredes and Rivera, 2017). Furthermore, most studies primarily examine short-term outcomes, only observing a few years after a commodity boom or resource discovery. As a result, it becomes challenging to determine whether the lack of significant impacts is due to delays in project implementation and maturity, or reflects more profound issues such as corruption or limited technical capacity. Nonetheless, addressing this question is crucial for assessing the overall impact of extractive industries and can provide insights for decentralization and extractive policies.

This study analyzes the long-term consequences of a resource-based windfall on local living conditions. Our focus is on the Peruvian canon, a resource-based transfer to local governments funded by taxes paid by mining and other extractive industries. While previous research has examined the impact of the canon, the findings remain inconclusive. Some studies indicate no significant effects on income, poverty, or inequality, while others highlight a positive or even non-monotonic relationship (Loayza and Rigolini, 2016, Maldonado, 2014, Zambrano et al., 2018).

To conduct our empirical analysis, we use multiple data sources at the municipality level, including Population Censuses, poverty maps, municipality surveys, and financial records. Unlike previous studies, our research incorporates a longer time span, encompassing the years 1993 to 2017 for certain variables. By harnessing the richness of this data, our study examines the effects of the canon on various indicators of living standards, such as the availability of public services, poverty levels, and inequality. Importantly, we assess these impacts over a decade after the commencement of the commodity boom, providing valuable insights into the long-term implications of the canon.

A crucial empirical concern, as recognized in previous studies, is that resource-based transfers are not randomly distributed and may be influenced by unobservable characteristics. We employ several distinct but complementary identification strategies to address this endogeneity concern. Firstly, we estimate a cross-sectional Ordinary Least Squares (OLS) model incorporating a comprehensive sociodemographic and geographical control set. Secondly, we leverage the features of the allocation formula, which generate variation across administrative boundaries. Thirdly, we employ a propensity score matching approach similar to the one used by Loayza and Rigolini (2016). Lastly, we utilize panel data to implement a long difference-in-differences approach while accounting for municipality-fixed effects.

We observe significant effects on the resources available to municipalities. Notably, there is a substantial increase in fiscal revenue, the number of municipal workers, and municipalities' procurement of vehicles and heavy machinery. Additionally, we find suggestive evidence of increased investment directed toward transport infrastructure, such as urban roads and sidewalks. These findings indicate that the canon has had a tangible impact on allocating resources to local governments.

We find, however, no substantial evidence of a significant impact of the canon on measures of living standards. Firstly, we concentrate on the coverage of public services, including piped water, indoor sanitation, and electricity, which fall under the responsibility of local governments. Secondly, we investigate other potential well-being indicators, such as poverty rates and the Gini index. In all cases, the effect of receiving higher levels of canon is statistically insignificant. This finding remains robust across different model specifications and identification strategies and is not attributed to a lack of statistical precision. Moreover, the estimated effect size is generally small and, in some instances, even negative.

We interpret the results as evidence that the additional revenue generated from resource-based transfers has primarily been channeled toward infrastructure projects and increased expenditure on personnel and equipment by municipalities. However, we observe that the impact on observable measures of living standards is negligible. These results suggest that the observable social returns of the canon may have been relatively small and highlight the need to re-assess the role of resource-driven windfalls on local economic development.

# 2 Background

During the last two decades years, Peruvian local governments have experienced a dramatic increase in revenue (see Figure 1). For instance, from early 2000 to 2018, the budget of the average district municipality more than tripled, from around 3 million Nuevos Soles (PEN) to almost 18 million.

Most of this increment has occurred in the last ten years, fueled by Central government transfers linked to natural resources, such as the *canon*. The canon is a revenue-sharing scheme in which a fraction of the national corporate tax paid by extractive firms (mining, oil and gas, logging, and fishing) is allocated to local governments. This source of revenue increased substantially at the end of the 2000s due to the increase in commodity prices and extractive operations. As a result, in a couple of years (from 2007 to 2009), the value of the canon transfer almost doubled, and during the last decade, the canon has represented almost 40% of the total funds available to Peruvian local governments.

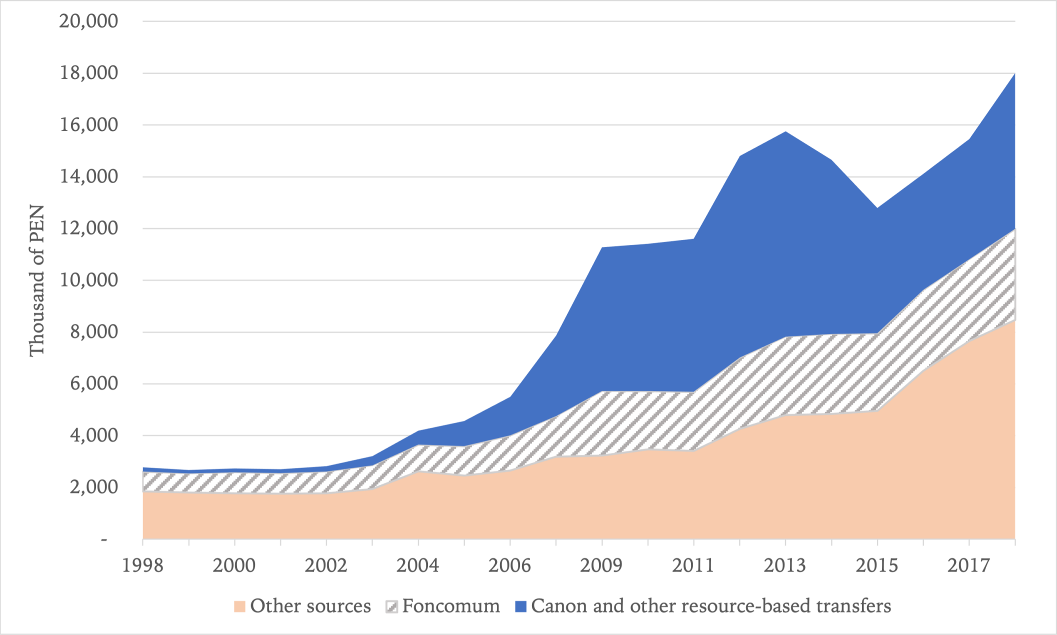
The canon is allocated using a formula based on indicators of population, needs, and geographical proximity to the resource. In particular, it is only distributed to municipalities located in the region where the resource is located. Municipalities in the province and district receive increasingly higher per capita amounts.

This feature of the allocation formula creates variation in the amount of canon along regional boundaries: adjacent municipalities can receive substantially different amounts of transfers depending on their side of the regional boundary. We exploit this geographical variation in one of our identification strategies.

The allocation formula also creates an unequal distribution of resource-based transfers (see Figure 2). For instance, between 1998 and 2016, the top 10% district municipalities received per capita canon almost nine times the median municipality. This outcome may have been intended in order to compensate municipalities more directly affected by the extractive activities.

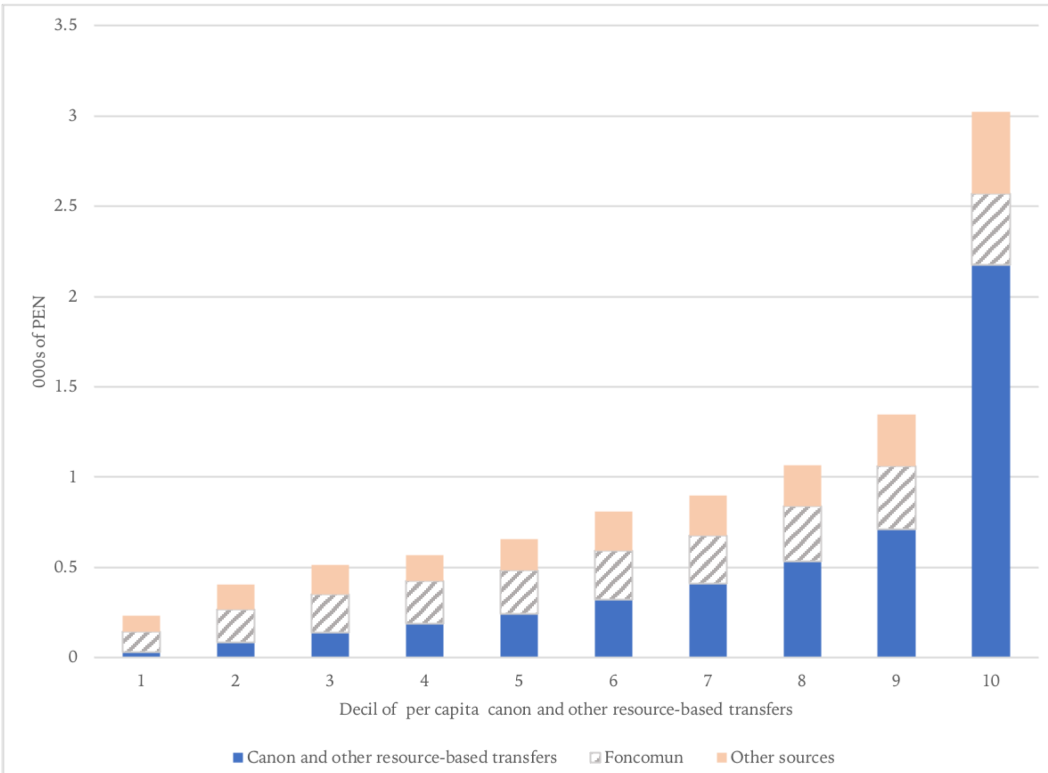
However, the inequality in the allocation of the canon has not been offset by equalization grants, such as the Foncomun (*Fondo de Compensacion Municipal*) or other revenue sources. As a result, there have been significant disparities in municipal total revenue. For example, the top 10% canon recipients have a per capita total revenue five times the median municipality and almost ten times the bottom 10%.

Figure 1: Average municipal revenue 1998-2018, by source




Notes: Figure depicts annual revenue (in thousands of PEN) from 1998-2016 for the average district municipality. The sample includes all district municipalities.

Figure 2: Municipal revenue per capita 1998-2016, by canon deciles




Notes: Figure depicts annual revenue per capita (in thousands of PEN) in the period 1998-2016 for the ten deciles of canon per capita. Deciles were obtained using average canon per capita from 1998-2016, and the same sample of municipalities included in regression analysis. Decile 10 corresponds to municipalities with the top 10% highest canon per capita.

# 3 Methods

## 3.1 Data

We construct a rich panel dataset at the district municipality level combining multiple data sources: Population Censuses, poverty maps, local governments' financial records, and municipality surveys (*Registro Nacional de Municipalidades* - Renamu).

Our primary outcomes are measures of 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 estimates of poverty and inequality at the district level. These variables are obtained from the Census and poverty maps constructed by the Peruvian Statistics Agency (INEI) using household surveys and Census microdata.

We also examine ancillary outcomes directly linked to local government operations, such as investment in local transport infrastructure (i.e., area of roads and sidewalks built or repaired) and municipalities' inputs (like the number of workers, cars, and heavy machinery, or self-reported needs of technical assistance). This data is obtained from several rounds of the Renamu survey. We complement these data with information on municipality demographic and geographical characteristics (such as altitude, average slope, and terrain ruggedness) and data from municipal budgets.

The budget data contains information on revenue from different sources including own revenues (taxes, contributions, and fees), the *Foncomun*, a large equalization grant, credit, and transfers. This last category includes resource-based transfers, like the canon. We cannot disentangle, however, the canon from *Participation de Renta de Aduanas*, a tax-sharing scheme linked to custom duties. To address this data limitation, we exclude from the sample observations from Callao, Tumbes, and Tacna, regions with major entry points to international trade. We also exclude observations from Lima metropolitan area due to its significant tax and technical capacity differences.

For each outcome variable, we collect information for two periods: before and after the expansion of resource-based transfers that started in the late 2000s (see Figure 1). The exact dates are shaped by data availability. The earliest observation is from the 1993 Census, while data from the poverty map and Renamu are available since 2007 and 1999, respectively. The latest observations are for the years 2017-2018.

Our final dataset contains a panel of around 1,580 municipalities. Tables 1 and 2 present summary statistics for the pre and post-commodity booms (years 1993 to 2997 and 2008 to 2017, respectively. Additionally, we distinguish between municipalities with a high level of canon (top 25% of the per capita canon) or low (bottom 75%) (columns 2 and 3). We use this distinction as our baseline indicator of treatment status in our empirical analysis.

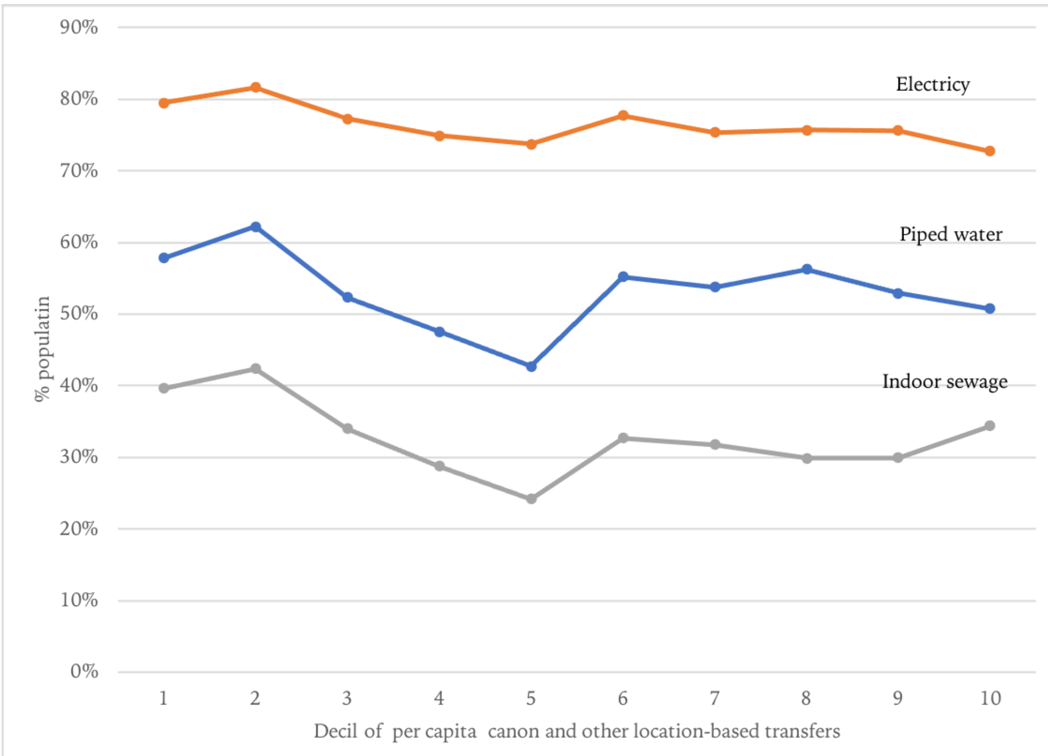
## 3.2 Identification strategies

A basic comparison of districts with high and low levels of canon suggests no sizable differences in measures of living conditions. For instance, Figure 3 shows the coverage of public services by decile of per capita canon. Note that deciles have similar access to piped water, indoor sewage, or electricity. We observe similar patterns using measures of poverty and inequality.

Although suggestive of a negligible impact, this evidence is not enough to assess the long-term effect of the canon. The main identification concern is the presence of systematic differences between municipalities with varied levels of transfers. As discussed in Section 2, the amount of transfers received by a municipality is a function of its proximity to the natural resource but also of the socio-demographic characteristics of the municipalities in its region. This issue creates scope for an omitted variables problem.

We address this issue using four alternative identification strategies. These strategies exploit our dataset's long-panel dimension and transfer-allocation formula features to reduce the scope for omitted variable bias.

Figure 3: Coverage of public services and canon per capita




Notes: Figure depicts average coverage of public services in 2017 by decile of canon per capita.

Table 1: Summary statistics (pre-commodity boom)

| Variable | All | Canon p.c. 1998-2016 | | p-value |
|---|---|---|---|---|
| | | Top 25% | Bottom 75% | (2)=(3) |
| | (1) | (2) | (3) | (4) |
| *Census 1993* | | | | |
| Rural population (%) | 0.605 | 0.637 | 0.593 | 0.013 |
| Population | 9,086 | 4,531 | 10,784 | 0.000 |
| % piped water | 0.197 | 0.161 | 0.210 | 0.000 |
| % indoor sanitation | 0.089 | 0.058 | 0.101 | 0.000 |
| % electricity | 0.244 | 0.197 | 0.262 | 0.000 |
| *Poverty map 2007* | | | | |
| Poverty rate | 0.598 | 0.629 | 0.588 | 0.001 |
| Gini index | 0.288 | 0.294 | 0.286 | 0.000 |
| *Municipal budgets 1998-2007* | | | | |
| Total revenue p.c. (000s) | 0.379 | 0.693 | 0.274 | 0.000 |
| Canon p.c. (000s) | 0.103 | 0.265 | 0.049 | 0.000 |
| *Renamu 1999* | | | | |
| No. workers (per 000s inhab.) | 3.131 | 3.819 | 2.875 | 0.007 |
| No. cars and truck (per 000s inhab.) | 0.125 | 0.178 | 0.106 | 0.010 |
| No. heavy machinery (per 000s inhab.) | 0.225 | 0.277 | 0.207 | 0.020 |
| No. automat. management tools | 0.622 | 0.473 | 0.675 | 0.001 |
| Need tech. assistance (index) | 0.640 | 0.638 | 0.641 | 0.842 |
| Need training (index) | 0.654 | 0.668 | 0.650 | 0.277 |

Notes: Table presents a simple average of variables over the sample of district municipalities. Columns 2 and 3 split the sample into treated and control groups. Column 4 displays the p-value of the mean comparison test. All monetary variables in Peruvian Nuevos Soles (PEN). p.c. = per capita.

The starting point is the following model :

$$y_i = \beta T_i + \gamma X_i + \epsilon_i \tag{1}$$

where the unit of observation is district municipality $i$. $y_i$ is the outcome variable, and $T_i$ indicates the municipality receiving a relatively high value of resource-based transfers. In our baseline specification, we define $T = 1$ if the average per capita transfer in the period

Table 2: Summary statistics (post-commodity boom)

| Variable | All | Canon p.c. 1998-2016 | | p-value |
|---|---|---|---|---|
| | | Top 25% | Bottom 75% | (2)=(3) |
| | (1) | (2) | (3) | (4) |
| *Geography* | | | | |
| Located in Highlands | 68.7% | 88.1% | 61.7% | 0.000 |
| Altitude (masl) | 2,645 | 3,317 | 2,420 | 0.000 |
| Ruggedness index | 77.2 | 91.8 | 72.3 | 0.000 |
| *Census and Poverty map 2017* | | | | |
| Population | 10,801 | 4,259 | 12,977 | 0.000 |
| % piped water | 0.532 | 0.523 | 0.534 | 0.426 |
| % indoor sanitation | 0.328 | 0.317 | 0.331 | 0.283 |
| % electricity | 0.764 | 0.745 | 0.771 | 0.003 |
| Poverty rate | 0.255 | 0.256 | 0.255 | 0.885 |
| Gini index | 0.192 | 0.189 | 0.193 | 0.013 |
| *Municipal budgets 2009-2017* | | | | |
| Total revenue p.c. (000s) | 1.668 | 3.561 | 1.038 | 0.000 |
| Canon p.c. (000s) | 0.959 | 2.523 | 0.439 | 0.000 |
| *Renamu 2018* | | | | |
| No. workers (per 000s inhab.) | 12.059 | 19.889 | 9.455 | 0.000 |
| No. cars and truck (per 000s inhab.) | 0.684 | 1.268 | 0.489 | 0.000 |
| No. heavy machinery (per 000s inhab.) | 1.486 | 2.749 | 1.065 | 0.000 |
| No. automat. management tools | 2.943 | 2.827 | 2.981 | 0.000 |
| Need tech. assistance (index) | 0.337 | 0.348 | 0.333 | 0.002 |
| Need training (index) | 0.396 | 0.400 | 0.395 | 0.308 |
| No. municipalities | 1,580 | 405 | 1,175 | |

Notes: Table presents a simple average of variables over the sample of district municipalities. Columns 2 and 3 split the sample into treated and control groups. Column 4 displays the p-value of the mean comparison test. All monetary variables in Peruvian Nuevos Soles (PEN) p.c. = per capita. The index of needs of technical assistance (training) is equal to the share of topics the municipality declares to need technical assistance (training).

1998-2016 (based on the 2017 population) is in the top quartile of the distribution.

Our first approach is to estimate 1 using OLS and adding a rich set of control variables $X_i$. As controls, we include sociodemographic characteristics in the baseline year 1993 (like population size, density, literacy, and the share of urban population), geographic features (altitude, slope, and terrain ruggedness), and region fixed effects (n=24).

Second, we exploit a feature of the allocation formula that creates geographical variation in the amount of canon received. The allocation formula assigns the resource-based transfers only to districts in the region where the natural resource is located. This allocation procedure creates variation in the transfer amount received by contiguous municipalities along a region's border. We identify the boundaries between two regions and the adjacent districts. Then we estimate equation (1) including a boundary fixed effect and restricting the sample to districts adjacent to a boundary.

Third, we use a propensity score matching approach. This semi-parametric approach compares outcomes between municipalities with similar probabilities of receiving high per capita levels of canon. Our strategy is similar to the methodology used by Ticci and Escobal (2015) and Loayza and Rigolini (2016) to study the impact of mining on poverty and inequality in Peru.[1]

Finally, we exploit the panel dimension and estimate regression (1) using $\Delta y_i$, the change in $y_i$ between the pre and post-boom periods, as the dependent variable. In the case of Census variables (like access to public services), this outcome corresponds to the change between 1993 and 2017. This fourth specification is a first-difference panel data model. Note, however, that this approach is equivalent to the following difference-in-difference (DiD) model with municipality fixed effects and heterogeneous time trends:

$$y_{it} = \beta(T_i \times D_t) + \gamma(X_i \times D_t) + \eta_i + \varepsilon_{it}$$

where $\eta_i$ is the municipality fixed effect, $D_t$ is a binary indicator of treatment equal to 1 if the period is the post-commodity boom, and $T_i$ indicates the treated or control group.

[1]We implement this approach using the STATA command *psmatch2*. The propensity score is based on the set of variables $X_i$, including geographic and socio-demographic characteristics from the 1993 Census.

# 4 Results

## 4.1 Main results

We find no evidence of statistically significant nor sizable improvement in measures of living standards (see Table 3). This result is robust across identification strategies and to changes in the baseline specification like using population weights, removing the sample restriction, or changing the definition of the treatment variable $T_i$ (see Table 4). Our results are not driven by the choice of outcome variables or lack of statistical power. Note that the points estimates are, in several cases, negative, which suggests a relative deterioration in coverage of public services and an increase in inequality. Thus, even more precise estimates would not alter our interpretation.

This finding is similar to evidence of negligible short-term effects of resource-based transfer on living conditions documented by (Aragón and Rud, 2013) and (Loayza and Rigolini, 2016) in the Peruvian context, and by (Caselli and Michaels, 2013) in the context of oil-rich Brazilian municipalities. They are also similar to some findings in the aid effectiveness literature suggesting that unconditional grants tend to have a limited impact on poverty and economic growth Doucouliagos and Paldam (2009), Rajan and Subramanian (2008)

A possible explanation of our null results is that our estimates hide treatment heterogeneity. For example, the impact of the canon may have been positive among certain types of municipalities with different socio-economic needs or technical capacity levels. By bundling all municipalities together, these positive impacts might have been diluted.

We examine this explanation by adding our treatment variable $T_i$ interacted with municipality baseline characteristics. These characteristics include indicators of being located in the highlands, having a higher share of rural population, having more self-reported technical needs or less educated population. The results in Table 5 show no apparent heterogeneous effects. The only significant impact seems to occur in the Gini coefficient (column 5), for which there seem to be differences between municipalities located in the Highlands vs. the rest of the country. This result, however, is not robust to corrections for multiple hypothesis testing.

Table 3: Effect on coverage of public services, poverty, and inequality

| Dependent variables | Identification strategy | | | |
|---|---|---|---|---|
| | OLS | OLS + boundary FE | Propensity Score Matching | Panel data DiD |
| | (1) | (2) | (3) | (4) |
| *A. Coverage of public services* | | | | |
| % piped water | -0.046*** | -0.048* | -0.007 | -0.016 |
| | (0.016) | (0.025) | (0.017) | (0.017) |
| % indoor sanitation | -0.022* | 0.012 | 0.031 | -0.020 |
| | (0.012) | (0.020) | (0.021) | (0.014) |
| % electricity | -0.024*** | 0.029** | -0.018 | 0.008 |
| | (0.009) | (0.015) | (0.014) | (0.016) |
| *B. Poverty and inequality* | | | | |
| Poverty rate | 0.003 | -0.002 | -0.020* | -0.003 |
| | (0.009) | (0.015) | (0.011) | (0.010) |
| Gini index | 0.003 | 0.005* | 0.004 | 0.004** |
| | (0.002) | (0.003) | (0.002) | (0.002) |
| No. obs. | 1,580 | 504 | 1,580 | 1,580 |

Notes: Robust standard errors in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Table displays estimates of $\beta$, the effect of receiving high levels of per capita canon on the dependent variable. Each estimate is obtained from a separate regression. Columns 1 to 4 show estimates using the alternative identification strategies described in Section 3.2.

## 4.2 Municipal resources and infrastructure projects

So far, our analysis has focused on end-point outcomes. In this sub-section, we focus on intermediate outcomes such as indicators of municipality resources (revenue, number of workers

Table 4: Robustness checks

| Dependent vars. | Robustness check | | | | |
|---|---|---|---|---|---|
| | Add pop. weights (1) | Treated = top 10% canon p.c. (2) | Using canon p.c 2009-2016 (3) | No sample restriction (4) | Continuous treatment (5) |
| *A. Coverage of public services* | | | | | |
| % piped water | -0.009 | -0.041* | -0.015 | -0.016 | 0.052 |
| | (0.021) | (0.023) | (0.018) | (0.016) | (0.038) |
| % indoor sanitation | 0.006 | -0.011 | -0.020 | -0.019 | -0.008 |
| | (0.018) | (0.018) | (0.013) | (0.013) | (0.029) |
| % electricity | 0.009 | -0.011 | 0.012 | 0.007 | -0.020 |
| | (0.021) | (0.023) | (0.016) | (0.015) | (0.038) |
| *B. Poverty and inequality* | | | | | |
| Poverty rate | -0.010 | -0.005 | -0.001 | 0.013 | -0.022 |
| | (0.012) | (0.013) | (0.009) | (0.009) | (0.020) |
| Gini index | -0.001 | 0.002 | 0.002 | 0.006*** | 0.005 |
| | (0.004) | (0.002) | (0.002) | (0.002) | (0.004) |
| No. obs. | 1,580 | 1,580 | 1,580 | 1,661 | 1,580 |

Notes: Robust standard errors in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Table displays estimates of $\beta$, the effect of receiving high levels of per capita canon on the dependent variable. Each estimate is obtained from a separate regression. All regressions use the DiD approach (as in column 4 in Table 3) but modify the baseline specification. Column 1 weights observations using the 2017 population size. Column 2 defines $T_i = 1$ if canon p.c. is in the top decile. Column 3 uses average canon p.c. in the period 2009-2016 to construct $T_i$. Column 4 eliminates the sample restriction. Column 5 defines $T_i$ as the proportion of years between 1998-20016 in which the municipality obtained a canon p.c. in the top quartile.

and equipment, and indicators of technical capacity) and infrastructure projects.

We corroborate that having received high levels of canon is associated with a substantial increase in total revenue (panel A in Table 6). There is also a significant effect on the relative number of workers and equipment (cars, trucks, and heavy machinery) owned by the municipality (panel B). The magnitude is sizable. For example, the number of workers

Table 5: Heterogeneous effects

| | Dependent variables | | | | |
|---|---|---|---|---|---|
| | % piped water (1) | % indoor sanitation (2) | % electricity (3) | Poverty rate (4) | Gini index (5) |
| $T_i$ = Top quartil of p.c. canon | -0.016 | -0.057 | -0.018 | -0.004 | 0.015** |
| | (0.043) | (0.045) | (0.050) | (0.021) | (0.006) |
| $T_i \times$ Highland | 0.018 | 0.044 | 0.051 | -0.023 | -0.012** |
| | (0.043) | (0.043) | (0.050) | (0.020) | (0.006) |
| $T_i \times$ high share rural pop. 1993 | 0.020 | 0.010 | -0.016 | 0.028 | -0.000 |
| | (0.036) | (0.025) | (0.029) | (0.018) | (0.003) |
| $T_i \times$ high needs of training or technical assist. 1999 | -0.032 | -0.003 | 0.002 | 0.003 | -0.004 |
| | (0.030) | (0.021) | (0.027) | (0.016) | (0.003) |
| $T_i \times$ below median % pop. complete high school 2007 | -0.026 | -0.010 | -0.024 | 0.011 | 0.004 |
| | (0.035) | (0.025) | (0.029) | (0.018) | (0.003) |
| No. obs. | 1,580 | 1,580 | 1,580 | 1,579 | 1,579 |
| R-squared | 0.159 | 0.234 | 0.407 | 0.484 | 0.595 |

Notes: Robust standard errors in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Each column displays the estimates of a regression model using the panel data DiD approach (column 4 in Table 3). $T_i$ indicates receiving high levels of per capita canon (top quartile). The regression includes interactions of $T_i$ with municipality characteristics like being located in the Highlands, having above the median share of rural population in 1993, having above median values in an index of needs of technical assistance, and having below the median share of working age population with complete secondary education in 2007.

per 1,000 inhabitants in the control group was 20, and the estimated effect is almost 6: an increase of 30%. There is, however, no significant improvement in measures of technology, such as the number of automated management tools or self-declared needs for technical assistance or training.

We also explore the impact of the canon on investment in transport infrastructure using indicators such as the area built or repaired of urban roads and sidewalks. We focus on transport infrastructure projects instead of other projects for three reasons. First, the construction and maintenance of local road infrastructure is a key activity of district municipalities. Second, the outcome is relatively homogeneous and thus comparable across localities. Finally, there is data availability: municipalities self-report the area of roads and sidewalks repaired in a given year. We use the cumulative area built or repaired in the period 2006-2018 as our main outcome variables and normalize them by the population size.

Table 7 shows that the relative amount of transport infrastructure (roads and sidewalks) built or repaired is larger for municipalities with high canon. The estimates are noisy and, in some cases, marginally significant (see column 3), but the magnitude is sizable. For instance, the increased area of roads repaired is almost twice the control group's mean.[2]

[2]Note that we only observe data on transport projects from 2006-2018. Thus, we cannot implement a DiD approach.

Table 6: Effect on municipality resources

| Dependent variables | Identification strategy | | | |
|---|---|---|---|---|
| | OLS | OLS + boundary FE | Propensity Score Matching | Panel data DiD |
| | (1) | (2) | (3) | (4) |
| *A. Fiscal revenue* | | | | |
| Total revenue p.c. (000s) | 2.016*** | 2.418*** | 2.329*** | 1.775*** |
| | (0.177) | (0.279) | (0.178) | (0.168) |
| *B. Workers and equipment* | | | | |
| No. workers (per 000s inhab) | 6.077*** | 5.571*** | 9.970*** | 5.545*** |
| | (1.137) | (1.300) | (1.996) | (1.176) |
| No. cars and trucks (per 000s inhab) | 0.450*** | 0.439*** | 0.440*** | 0.420*** |
| | (0.089) | (0.149) | (0.093) | (0.096) |
| No. heavy machinery (per 000s inhab) | 0.798*** | 0.809*** | 0.896*** | 0.752*** |
| | (0.148) | (0.219) | (0.108) | (0.154) |
| *C. Management and technical capacity* | | | | |
| No. automated management tools | -0.057 | -0.010 | -0.108 | -0.177** |
| | (0.055) | (0.087) | (0.076) | (0.088) |
| Requires technical assistance (index) | 0.005 | 0.001 | -0.017 | 0.003 |
| | (0.019) | (0.031) | (0.015) | (0.028) |
| Requires training (index) | -0.006 | -0.010 | -0.029 | -0.024 |
| | (0.020) | (0.033) | (0.020) | (0.030) |
| No. obs. | 1,580 | 504 | 1,578 | 1,580 |

Notes: Robust standard errors in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Table displays estimates of $\beta$, the effect of receiving high levels of per capita canon on the dependent variable. Each estimate is obtained from a separate regression using alternative identification strategies described in Section 3.2. Total revenue p.c. is calculated as the average in the period 1998-2007 and 2009-2016.

Table 7: Effect on investment on transport projects

| Dependent variables | Identification strategy: OLS (1) | OLS + boundary FE (2) | Propensity Score Matching (3) | Mean dep. variable control group (4) |
|---|---|---|---|---|
| Roads repaired | 2.408 | 4.492 | 1.943* | 1.073 |
| | (1.801) | (4.015) | (1.095) | |
| Roads built | 1.952 | -0.514 | 4.529* | 4.130 |
| | (1.689) | (1.546) | (2.367) | |
| Sidewalks repaired | 0.131 | 0.180 | 0.126 | 0.204 |
| | (0.166) | (0.219) | (0.186) | |
| Sidewalks built | 0.994 | -0.295 | 1.894* | 1.856 |
| | (1.820) | (0.857) | (1.066) | |
| Index of transport invest. | 1.371* | 0.966 | 2.123*** | 1.815 |
| (= avg. of all outcomes above) | (0.822) | (1.109) | (0.725) | |
| No. obs. | 1,580 | 504 | 1,580 | |

Notes: Robust standard errors in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Table displays estimates of $\beta$, the effect of receiving high levels of per capita canon on the dependent variable. Each estimate is obtained from a separate regression using alternative identification strategies described in Section 3.2. The dependent variables are the cumulative area of roads or sidewalks (repaired or built) from 2006-2018 (in squared meters) divided by the 2017 population.

# 5 Conclusion

This study investigates the long-term impact of the Peruvian canon on local living conditions. Our findings indicate no significant effects on access to public services, poverty levels, or inequality. However, we do observe observable effects on measures of municipal resources, such as personnel, vehicles, and transport infrastructure projects.

The lack of translation of additional resources into improved local living conditions can be attributed to several possible explanations proposed in previous research. These explanations can be broadly categorized into three groups.

Firstly, municipalities may lack the capacity to utilize the resources effectively. This could be due to a lack of qualified personnel for project design and implementation, the requirement of approval from other sub-national governments, or the presence of costly administrative procedures that hinder project development.

Secondly, local authorities may lack the incentive to utilize the resources for improving local living conditions. Instead, they may divert them for clientelism or personal gain. This political economy perspective, discussed in the work of Maldonado (2014), suggests a non-linear impact of the canon on public good provision. Similar findings have been reported in the context of oil-rich Brazilian municipalities by Caselli and Michaels (2013), who interpret the results as indicative of clientelism and corruption. Support for this interpretation comes from Brollo et al. (2013), who provide direct evidence that federal transfers increase local corruption and diminish the quality of politicians.

Lastly, local populations may prioritize the allocation of resources towards projects that do not directly translate into improvements in our measured living conditions. For example, Faguet (2004) shows that fiscal decentralization in Bolivia led to increased responsiveness to local needs and substantial changes in spending patterns.

Due to data limitations, we are unable to empirically examine these explanations. Nevertheless, irrespective of the underlying mechanism, our results suggest that the observable social benefits of the canon may have been minimal. This underscores the need to reassess the role of resource-driven windfalls in local economic development.

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