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by

Jorge M. Agüero
University of Connecticut

Carlos Felipe Balcázar
New York University

Stanislao Maldonado
Universidad del Rosario

Hugo Ñopo
Grupo de Analisis de Desarrollo

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365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

The Value of Redistribution: Natural Resources and the Formation of Human Capital under Weak Institutions

Jorge M. Agüero, Carlos Felipe Balcázar, Stanislao Maldonado and Hugo Ñopo*

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Abstract

We exploit time and spatial variation generated by the commodities boom to measure the effect of natural resources on human capital formation in Peru, a country with low governance indicators. Combining test scores from over two million students and district-level administrative data of mining taxes redistributed to local governments, we find sizable effects on student learning from the redistribution. However, and consistent with recent political economy models, the relationship is non-monotonic. Based on these models, we identify improvements in school expenditure and infrastructure, together with increases in health outcomes of adults and children, as key mechanisms explaining the effect we find for redistribution. Policy implications for the avoidance of the natural resource curse are discussed.

JEL Codes: H7, H23, I25, O15, Q32

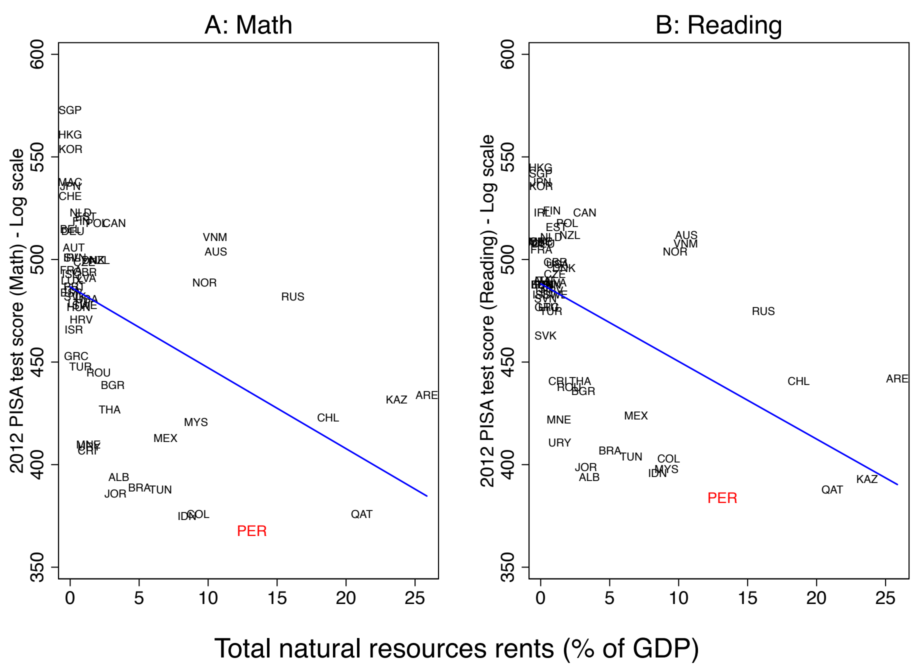
Key words: Resource booms, academic achievement, intergovernmental transfers.

* *Agüero:* Department of Economics and El Instituto, University of Connecticut, 65 Fairfield Way, Storrs, Connecticut, United States of America. *Balcázar:* Wilf Family Department of Politics, New York University, 19 West 4th St., 2nd floor, New York, United States of America. *Maldonado:* Department of Economics, Universidad del Rosario, Calle 12C No. 6-25, Bogotá, Colombia. *Ñopo:* Grupo de Analisis de Desarrollo, Av. Almirante Grau 915, Lima, Perú. We thank participants at LACEA-LAMES Annual Meetings, the Fiscal and Social Policy Global Solutions Group Seminars at World Bank, and the Economics Department Seminar at Universidad del Rosario for their useful comments. Juliana Aragón and Jostin Kitmang provided research assistance. Corresponding author at jorge.aguero@uconn.edu

1. Introduction

A long-standing question in the economics literature explores whether natural resource abundance is a curse or a blessing. The recent commodities boom has brought back this discussion. While the impact of such a boom on aggregate economic growth has been explored elsewhere,[1] the study of the linkages between the abundance of natural resources and human capital formation still requires deeper analysis. For instance, cross-country correlations indicate a negative relationship, suggesting that natural capital crowds out human capital (Gylfason, 2001; Birdsall et al., 2001).[2] As shown in Figure 1, there is a strong negative association between a country's reliance on natural resources and its performance on international standardized tests.

Figure 1. Natural resources and test scores



Note: Data for the test scores come from PISA 2012 and the share of GDP from total natural resources (2011-2012 average) comes from the World Bank's World Development Indicators (code: NY.GDP.TOTL.RT.ZS) and represents the sum of rents from oil, natural gas, coal (hard and soft), mineral, and forest. Data for this graph can be downloaded from http://www.oecd.org/pisa/ and http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

[1] See Aragón et al. (2015), Ross (2015), van der Ploeg (2011), Deacon (2011), Rosser (2006) and Stevens (2003), for comprehensive literature reviews.

[2] There is also evidence that good political institutions can ameliorate this outcome (Kronenberg, 2004; Gylfason and Zoega, 2006).

Along these lines, within-country studies using microeconomic data exploit a single-commodity boom, such as coca in Colombia (Angrist and Kugler, 2008) and oil in Brazil (Caselli and Michaels, 2013), and document some positive but modest impacts of natural resource abundance on school attendance and attainment, as well as on literacy rates. While important, much remains to be done given the increasing emphasis on learning outcomes. Indeed, the quality of education in developing countries remains below par (Hanushek and Woessmann, 2010; Kremer et al, 2013). Furthermore, differences in the *quality* of education appear to be more important than access to education when explaining countries' economic performance over the past fifty years (Hanushek and Woessmann, 2012). Thus, a pending question centers on whether natural resource abundance affects human capital accumulation beyond traditional measures, towards indicators such as those test scores and used in Figure 1.[3]

We address this gap by analyzing the impact of natural resource abundance on students' math and reading skills in Peru, a mineral-rich middle-income country that consistently underperforms in the World Bank's governance measures relative to their geographical and income-level counterparts (Kaufmann et al, 2011). Specifically, we inquire about the role of the *redistribution* of natural resource rents on learning outcomes. In this regard, our study informs an ongoing debate about whether the provision of additional resources to public schools improves students' learning outcomes (e.g., Hanushek, 2006; Glewwe and Kremer, 2006; Glewwe and Muralidharan, 2016; Jackson, 2018).

Peru offers a unique opportunity to evaluate this question. First, Peru has near-universal school enrolment yet it shows poor results in international achievement tests (see figures above) as well as in the national standardized tests such as the *Evaluación Censal de Estudiantes* (ECE).[4] Improving students achievement is a major way to address the learning crisis in developing countries (World Bank, 2018; Busso et al., 2017). We use math and reading test scores from Peru's

[3] Recent work by Bonilla (2020) focuses on a single commodity (gold in Colombia) and finds a *negative* effect on learning from this natural resource.

[4] The country is consistently one of the worst performing nations in the Programme for International Student Assessment (PISA) that includes OECD and developing countries. Peru is also the second from the bottom among countries in the Latin American Laboratory for Assessment of the Quality of Education, performing only better than the Dominican Republic.

ECE (2007-2012) for second graders as proxies for human capital accumulation, focusing on quality measures (output) rather than access (input).

Second, mining revenues constitute around half of the taxes collected by Peru's central government and these revenues have been partially redistributed to local governments.[5] This transfer is the result of the *Canon Minero Law* (from here on *Canon*), introduced in 2001. The law states that 50 percent of the income tax paid by mining companies to the central government must be redistributed to the regional and local governments located in the areas where minerals are extracted. This legal framework also establishes a redistribution-rule that grants transfers to non-producing districts located in the same region of the producing districts. Key to our identification strategy, the redistribution rule was defined prior to our period of analysis and has not been modified since. Thus, for a given district, we study the link between test scores and the year-by-year variation in transfers received by the district's local government.[6] To do so, we match a unique administrative dataset collecting the redistribution to each local governments with close to 2.1 million student records obtained from the national standardized test mentioned previously.

By conditioning on district fixed effects, and in additional specifications by province-by-year fixed effects as well, our parameter of interest is identified from district-specific deviations in transfers from the district averages after controlling for shocks common to all districts in a province. Given that the amount of *Canon* collected depends exclusively on external factors related to global trade (through the value mining production, a variable included in our controls) and not due to local markets, it seems reasonable to presume that *Canon* fluctuations are orthogonal to unobserved determinants of test scores for second graders.

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[5] During the period of our analysis (2007-2012) the country exported over 127.9 billion US dollars in minerals. The sector accounts for nearly two-thirds of the value of country's exports. However, the country does not rely on just one mineral. Peru is one of the world top producers of silver, tin, zinc, copper and gold, oil and gas are of little relevance (USGS, 2015). As a result, there is time and spatial variation in the value of mining production over a wide set of minerals (see Figure A1 and A2 in the Appendix). Importantly as well, Peru's mining sector is traditionally export oriented, since Colonial times (Dell, 2010), with most of its production being shipped directly overseas (Osinergmin, 2017).

[6] During the period of analysis, the sum of *Canon* transfers was 8.9 billion US$. In 2012 alone, the central government transferred US$1.9 billion as *Canon*; six times the budget allocated to the country's antipoverty conditional cash transfer program (*Juntos*) and 1.8 times the entire budget of the Ministry of Social Development, which is in charge of all welfare programs. *Canon* transfers also differ significantly even among the top recipients over our period of analysis. See Appendix Figure A2 for an example of this variation.

Our findings reveal that *Canon* transfers have a positive and statistically significant effect on math test scores. For the average district receiving a positive transfer, our estimates suggest an increase in math test scores of around 0.24 standard deviations. These effects are larger than most of the interventions using randomized controlled trials considered in Kremer et al. (2013). For reading, we find smaller (and sometimes negative) effects, but they are not statistically significant. These findings remain unchanged when considering several robustness tests, including controls for the value of mining production. Furthermore, two placebo tests validate our approach: a falsification exercise where we incorrectly assign *Canon* transfers of one district to a randomly selected district in the country, as well as a placebo test limiting the sample to private schools. As expected, both tests show no impact on students' academic achievement, reinforcing the validity of our approach.

Following the political economy literature (e.g., Caselli, 2015; and Caselli and Cunningham, 2009), we test for the presence of non-monotonic effects of *Canon* transfers. Resource booms could affect the behavior of the local incumbent in a non-monotonic fashion (Maldonado, 2020). Political competition rises as natural resource rents increase and this competition could work as a discipline device, creating incentives for investments in public goods provision such as human capital. At low rents levels, the outside option for potential politicians is higher than the rents they could extract while in office, so challenging the incumbent is less attractive and deters the entrance of a political competitor. In this scenario, incumbents can use *Canon* transfers to provide public goods (such as investing in human capital) because the lack of challengers disincentivize buying-off citizens' electoral support or coercing political competition. This behavior continues even as more resources become available, as long as these rents are lower than the opportunity costs outside political office, so higher *Canon* rents still translate into more public goods investments. However, when natural resource rents are too high, the value of holding office increases so much that it dominates the opportunity cost of staying out of politics. This motivates potential politicians to challenge the incumbent. In this scenario, incumbents would prefer to reduce the investment in public goods and instead influence electoral outcomes by buying-off citizens' electoral support and coercing political competition. This model would predict an inverted-U relationship between natural resource windfalls and public spending (e.g., public spending in education). This would be the key mechanism behind a non-monotonic relationship between natural resource rents and children educational outcomes. Only with very large natural resources windfalls have detrimental effects on human capital— creating a natural resource curse.

We find evidence in favor of these predictions and document a non-monotonic effect on learning outcomes. We show that a quadratic model fits the data best compared to linear, cubic and quartic specifications. We use additional administrative data to explore some of the mechanisms behind our findings. For instance, we show that year-to-year variation in *Canon* transfers is associated with higher expenditure on education at the level of the local government, a result consistent with the aforementioned mechanism. We complement this with an analysis at the school level, where we find that *Canon* transfers lead to positive investments in public-school infrastructure (e.g., electricity and sanitation). We do not observe changes in school enrollment, ruling out the possibility that the impact of *Canon* transfers on test scores is driven by population effects (i.e., areas with larger windfalls attracting or repelling families with children). We use household surveys to explore additional mechanisms and find strong evidence that health outcomes of adults and children are also potential mechanisms for the impact we find for redistribution.

Our findings contribute to the recent literature exploring the effects of resource windfalls on the behavior of the local government.[7] Caselli and Michaels (2013) show that oil-rich municipalities in Brazil increase their spending on public goods, but they find mixed results on welfare-relevant outcomes such as household income. Rather, the authors argue that municipal officials used public funds for patronage, rent sharing and possible embezzlement. Unlike Brazil, *Canon* transfers in Peru seem to be less likely to generate malfeasance. Maldonado and Ardanaz (2020) show that districts benefiting from *Canon* transfers in Peru were more efficient in their use of the fiscal windfalls. Furthermore, Loayza and Rigolini (2016) and Zambrano et al. (2014) show that areas benefiting from Peru's mining boom and *Canon* transfers saw significant reductions in their poverty levels. While we cannot properly test it within our framework, it is possible that strict regulations limiting the use of *Canon* resources explain the differences between our results and

[7] They are also related to a vast literature evaluating the effect of school resources on student performance (e.g., Hanushek, 2006; Jackson, 2018).

those of Caselli and Michaels (2013).[8] The work by Bonilla (2020) points to that direction. He shows that in the context of illegal and small-size gold mining in Colombia, windfalls lead to more revenue, but it does not translate into more education spending. Our findings show in contrast, that a natural resource boom can lead to an increase of human capital accumulation when adequate institutional mechanisms for the distribution of natural resource windfalls are in place.

The rest of the paper proceeds as follows. In Section 2 we briefly describe the institutional setting of the Peruvian *Canon* law. In sections 3 and 4, respectively, we present the data sources and the identification strategy. In Section 5 we present our results, including our robustness checks. In Section 6 we summarize our findings.

2. Local transfers in Peru: The Case of the *Canon Minero*

Several countries have implemented mechanisms that share the taxes and royalties paid by extractive companies with subnational governments. This has been associated with an important expansion of fiscal resources in resource-rich countries, creating opportunities to improve the living conditions of citizens (Brosio and Jimenez, 2012). In Peru, the Law 27506 or *Ley del Canon* (*Canon* Law), approved in 2001, mandates that part of the income tax paid by mining companies should be allocated to the regional and local governments located in the areas where minerals are extracted.

The *Canon* Law was not related to the commodity boom—increases in mineral prices would take place later in the decade—but rather was implemented as part of the country's decentralization process during the final days of the transitional government.[9] After several amendments to the original law,[10] it was established in 2004 that the *Canon* should be 50% of the income tax and that

[8] Maldonado (2020) argues that corruption can hardly explain the lack of effects because politicians cannot steal the whole budget without facing consequences. The lack of effects is more likely a consequence of a failure to consider the non-monotonic effects suggested by the theoretical literature.

[9] This law has as a historical antecedent: The Oil *Canon*, which was established in 1976 during the military government through Decree-Law 21678 after the discovery of oilfields in the Peruvian Amazon. It was later modified in 1992 to include mining activities and stated that 20 percent of the income tax should be allocated to the areas in which the profits were generated. The *Canon* Law explored in our paper was established by the government of President Valentín Paniagua, who came to power after Alberto Fujimori resigned from the presidency in September of 2000.

[10] The original law of 2001 established that 20 percent of the transfers should be assigned to the municipalities of the province where the mineral is extracted, 60 percent to the other provinces in the region and the remaining 20 percent

it should be distributed depending on whether districts are producers of a mineral or not. To help guide our description, please note that Peru is divided into *regions*, which in turn are divided into *provinces,* which are divided into *districts (municipalities)*.[11] The law established that 10% of the *Canon* goes directly to the producing district, that is, the municipality where the resources are obtained. The law also establishes that if the mineral is extracted in more than one district, the *Canon* is distributed among these producing districts proportionally to the corresponding sales specified by mining companies. Non-producing districts located in a producing province get 25%. Local governments located in non-producing provinces get 40% and the regional government where the mineral is extracted receives 20%. The remaining 5% goes to public universities of the region.

The law requires the Ministry of Finance to distribute the *Canon* using a poverty index in a progressive way (with higher weight to poorer districts) but only among *non-producing* districts. The index uses information from the Population Census, Agricultural Census, Census of Children Heights (for primary school children), District Registry and the district's altitude above sea level. Two features of the poverty index help validate our identification strategy. First, none of these variables are based on students' test scores. This helps us rule out the possibility that the transfers are allocated based on test scores as a compensating or rewarding scheme. Furthermore, the values included in the index are fixed and were set before the start of our period of analysis. For instance, the Agricultural Census is from 1994, the Census of Heights from 2005 and the Population Census from 2007.[12] Yet, the existence of the poverty index demands that in all our regression models we control for district fixed effects as we do. Our identification strategy relies on the year-to-year variation in the *Canon* transfer, within the same district and whose weight in the allocation of the *Canon* remain fixed over the years.

From a fiscal perspective, local governments in Peru play a very marginal role as the central government collects 97% of all taxes (Polastri and Rojas, 2007). Local governments' ability to

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to the regional government. This was changed in 2003 (Law 28077) and again in 2004 (Law 28322) where the distribution applied during our period of analysis was established.

[11] Peru is divided into 24 political regions, which in turn are divided into 196 provinces and into over 1,867 districts or municipalities.

[12] These datasets were not updated until after the end of analysis period (2017 for Population Census, 2012 for Agriculture and the Census of Heights was never updated. Also, as we describe later, we extend the model by including province-specific trends and our results are robust to that inclusion. Note also that our period of analysis comprises 2007, thus we perform a robustness test excluding 2007 and our main results remain unchanged (Table A15).

establish taxes or marginal rates is very limited. Property taxes (vehicles, real estate and real estate transfer) are the main source of local tax revenues for Peruvian municipalities (90% of their budget in 2007, the starting year of our analysis), while production and consumption taxes play a small role, representing at most 13% of local governments' current incomes (Calvo-Gonzalez et al., 2010). Consequently, local governments are highly dependent on central government transfers, representing three-fourths of the local government budget (Canavire-Bacarreza et al., 2012).

Around one-third of these transfers are universally distributed among local governments through the "Fondo de Compensación Municipal" (Municipal Compensation Fund); while the rest are allocated as targeted transfers. From these targeted transfers, *Canon* (which may come from mining, oil, hydropower, forest and gas) represents a 91% of the total targeted transfers, the mining *Canon* being the most important one (72% of all *Canon* transfers, representing 29% of local governments' budgets). In some mineral-producing districts, *Canon* can account for as much as 70% of municipal budgets (Canavire-Bacarreza et al., 2012).

By law, mining *Canon* transfers can only be used for investment. This means that any project to be financed with *Canon* funds has to follow the rules of the Public Investment National System (SNIP, for its acronym in Spanish) and obtain the approval of the Ministry of Economy and Finance. The law also prohibits recurring expenses, such as payroll within the local government. These restrictions limit the capacity of local governments to allocate *Canon* funds to rent sharing and embezzlement (Maldonado, 2020), in contrast to the Brazilian experience reported by Caselli and Michaels (2013). This of course does no eliminate attempts, albeit unsuccessful, to circumvent these restrictions (Arellano-Yanguas, 2011; Maldonado, 2020).

3. Data and Descriptive Statistics

This paper combines many large administrative data sources and multiple household-level surveys to estimate the effect of *Canon* transfers on test scores, and to identify some of the important mechanisms that could lie behind any significant relation. The first dataset is the *Evaluación Censal de Estudiantes* (or ECE for its Spanish acronym). This a national standardized test applied yearly since 2007 to *all* second graders in Peru (the only grade for which this test is taken) in public and private schools.

Administered by the Ministry of Education, the ECE collects information about the students' performance in math and reading (with possible scores ranging between 0 and 800 in each subject) plus a small set of students' and schools' characteristics (e.g., gender, mother tongue and type of school). These test scores are our main outcome variable.[13]

Combining the tests scores from the ECE 2007 to 2012, our final sample contains over 2 million student records nationwide.[14] Our sample includes all rural areas. We also include urban areas, except for the capital cities in each of the 24 regions. The exclusion of these largest cities reflects the different social dynamics triggered by mining in these areas compared to rural and smaller cities (Mendez et al., 2006; Arellano-Yanguas, 2008).

Our second data source, the *Censo Escolar* (CE), allows us to use yearly information about schools in terms of infrastructure, personnel and other administrative data. These include the share of the teacher body with long-term contracts, access to electricity, water and sanitation, among others. As explained in the next section, we use some of these variables as additional controls (e.g., length of the school day, school administration, and percentage of girls enrolled) while others allow us to explore possible mechanisms (e.g., infrastructure and school personnel).

We merge these datasets with yearly district-level data of mining production and *Canon* transfers. We obtain data on the value of mining production from the annual reports of the Ministry of Energy and Mining. We convert the reported volumes of copper, tin, iron, zinc, molybdenum, silver, gold, tungsten and cadmium, at the district level, into U.S. dollars using current international prices of the corresponding minerals. *Canon* transfers are the monetary amounts that each district receives annually from the central government. The Ministry of Finance compiles, computes, and reports these figures based on the amount of mining production in the districts themselves. This

[13] The *Evaluacion Censal de Estudiantes* is the annual standardized test that since 2007 has evaluated learning goals for students in second grade in mathematics and reading. With more than a decade of experience, the standardized evaluation has been built on international state-of-the-art knowledge, following best practices of the community of practitioners and receiving advice for international experts. All this is possible, to an important extent, thanks to the participation of Peru in OECD's PISA. ECE takes place at the end of the school year (mid-November to early December) and has a very high coverage of schools (93%) during our period of analysis. For further details see Ministerio de Educación (2017). Finally, unlike GPA, which is determined by teachers, ECE is conducted and supervised by external proctors, who do not belong to the school. Teachers are not allowed to talk or help students during the exam and are not even permitted to see the actual test.

[14] This period of analysis is chosen to avoid dealing with rewards to schools or teachers tied to students' performance, or even anticipation of such rewards. Indeed, starting in 2014 results from ECE were used to allocate resources to schools, two years after our sample ends, therefore it is also safe to rule out even anticipatory behavior.

Ministry is also the source of the expenditure data by local governments on education (and culture) per year. We also convert government transfers into U.S. dollars using nominal exchange rates. We set all monetary values to 2010 prices using the U.S. consumer price index and express them in thousands of dollars per capita.[15]

Our fifth and final dataset allows us to explore other possible mechanisms, but at the household level. We use the repeated cross-sections from 2007 to 2012 of the *Encuesta Nacional de Hogares* (ENAHO), a nationally representative household survey yearly conducted by the Peruvian National Bureau of Statistics (INEI, for its acronym in Spanish) aimed at measuring living standards. ENAHO allows us to estimate the effect of the mining *Canon* transfers on health outcomes of children and adults, their caretakers.

Table 1 presents summary statistics for inputs and outputs. To facilitate the presentation, we partition the sample into three groups: producing districts, non-producing districts located in producing provinces, and non-producing districts in non-producing provinces. This classification follows the division created by the *Canon* Law. The table shows that districts in producing provinces, columns 1 and 2, present higher scores in math and reading on average than other districts, as well as a higher proportion of schools with access to basic services and with better teacher-related outcomes. It also shows that non-producing districts in producing provinces show better outcomes than their counterparts, with mining activities, despite *Canon* transfers are higher for the latter, suggesting the possible presence of non-monotonic effects.

Table 1. Descriptive statistics. Averages 2007-2012

	Producing districts	**Non-producing districts in producing provinces**	**Non-producing districts in non-producing provinces**
A. Test scores (*Evaluación Censal de Estudiantes*)			
Average score in mathematics	517.06	534.04	509.18
	(103.26)	(107.72)	(105.95)
	[53, 944]	[53, 944]	[53, 944]
Average score in reading	514.73	532.49	508.47
	(85.7)	(91.19)	(91.17)
	[62, 814]	[49, 814]	[49, 814]

[15] To obtain per-capita values, we divide the values of *Canon* transfers and production by population size estimates at the district level obtained from the Peruvian National Bureau of Statistics (INEI).

Number of students	*110,885*	*411,275*	*1,565,264*
B. Schools' characteristics (*Censo Escolar*), percentage			
Teachers with long-term contract	28.56	31.22	27.79
	(36.29)	(40.02)	(38.48)
	[0, 100]	[0, 100]	[0, 100]
Teachers with a tertiary education degree	1.11	1.42	1.55
	(7.88)	(7.94)	(8.93)
	[0, 100]	[0, 100]	[0, 100]
Teachers with a tertiary education degree from a school teaching program	97.44	97.08	94.54
	(11.36)	(11.09)	(17.08)
	[0, 100]	[0, 100]	[0, 100]
Schools with access to electricity	71.24	74.96	60.48
	(45.27)	(43.33)	(48.89)
	[0, 100]	[0, 100]	[0, 100]
Schools with access to water	65.86	68.97	54.98
	(47.42)	(46.26)	(49.75)
	[0, 100]	[0, 100]	[0, 100]
Schools with access to sanitation	74.83	76.45	72.12
	(43.41)	(42.43)	(44.84)
	[0, 100]	[0, 100]	[0, 100]
Number of schools	*5,811*	*24,534*	*83,330*
C. Districts' characteristics			
Mining production per-capita†	62		
	(224.99)		
	[0, 2494.75]		
***Canon* transfers per-capita**†	0.37	0.12	0.04
	(0.96)	(0.39)	(0.1)
	[0, 9.71]	[0, 10.15]	[0, 1.36]
Number of districts	128	554	1,156

† Thousands of U.S. dollars at constant prices of 2010, divided by total population in the district level.

Note: standard deviation in parenthesis. Minimum and maximum values in brackets. Population figures for each district and year are obtained from Peru’s National Bureau of Statistics (INEI).

Source: Authors’ calculations based on data from Peru’s Ministries of Education, of Finance, of Energy and Mines, and INEI.

4. Identification Strategy

We exploit variation across districts and time in the *Canon* transfers. Our main specification is given by:

$$y_{isdt} = \alpha + f(c_{dt}) + \delta_1 D_{dt} + \delta_2 X_{isdt} + \delta_3 S_{sdt} + \gamma_d + \theta_t + \varepsilon_{isdt} \quad (1)$$

where y_{isdt} is the test score for the student i, enrolled in school s, located in district d observed in year t; c_{dt} is the amount of *Canon* transferred to district d in year t, expressed in thousands of US dollars per-capita at constant prices of 2010. *Canon* transfers depend on the value of taxes paid by mining companies –which in turn depend not only on the value of production (determined by international prices) and the mineral produced in the locality—but also on the rules of the transfers discussed in Section 2. Thus we exploit year-to-year variation in the amount of *Canon* transfers received by the same district correlates with students' test scores conditional on D_{dt}, a vector containing the value of mining production and two dummies for whether the district is a producer or a non-producer in a producing province. Finally, X is a vector of socio-demographic characteristics of the student including gender and mother tongue; S is a vector of schools' characteristics. These characteristics include length of the school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), school type (one-teacher school/full grade) and percentage of girls enrolled in the school. γ_d and θ_t denote district and year fixed effects respectively. ε_{isdt} is an idiosyncratic error term. Standard errors are robust to unknown forms of heteroskedasticity and clustered at the district level.

As discussed in the introduction, models about the political economy of natural resources predict non-monotonic relationships (e.g., Caselli, 2015; Caselli and Cunningham, 2009). In the next section, we show that a quadratic model is preferred by specification tests compared to alternative models with higher or lower order polynomials.

A possible threat to our identification strategy is that *Canon* transfers could be correlated with unobserved variables that affect test scores, if for instance, larger transfers are disproportionally sent to poor performing districts. In that case, our estimates of $f(c_{dt})$ could be biased. This bias could also appear given that non-producing districts get more transfers based on their poverty status, as explained in the previous section. In such a case, if poverty is a strong predictor of low school performance our estimates could be biased. However, we are able to avoid both sources of bias by focusing on within-district variation in the *Canon* transfers given the inclusion of district fixed-effects (γ_d) in Equation (1), which control for the effects of distribution rule we just referred to. Therefore, our identification comes from year-to-year changes in the value of production in the same district.[16] Thus observed and unobserved time-invariant features are controlled for. As shown in Panel B of Appendix Figure A.2, there is substantial variation in *Canon* transfers even among the top receiving districts during our period of analysis. Also, the inclusion of time fixed effects allows us to control for the possibility that unobserved factors alter test scores and *Canon* transfer (as well as transfers) over time non-linearly. Furthermore, as part of our robustness checks, we expanded the model by including province by year fixed effects (see Appendix Table A14). This allows us to account for time-variant characteristics (observed and unobserved) by province. Therefore, as the amount of *Canon* collected depends exclusively on external factors related to global trade (through the value mining production) and not due to local markets, it seems reasonable to presume that *Canon* fluctuations are orthogonal to unobserved determinants of test scores for students in second grade.

Another potential threat to our estimation comes from the possibility that that local governments may influence production decisions by investing in ways that attract mining companies. As explained before, if the traits influencing investment decisions are time-invariant our district fixed-effect model will account for such characteristics. Also, the fact that starting a new exploitation requires seven years, on average, reduces the possibility that such traits drive our findings (Maldonado, 2020). Indeed, a new exploitation that started as a consequence of the mining boom would appear only at the end or after our period of analysis. Furthermore, by law, local governments play no role in the process of granting mining rights. Thus, it is unlikely that our findings are affected by local governments influencing production decisions.

Barrantes et al. (2010) show that changes in the mining *Canon* Law were the product of circumstantial alliances between congressmen from mineral rich regions and not the result of pressure from regional and local actors or the executive power. However, these negotiations and changes in the law, took place in 2004, that is three years *before* our period of analysis. Moreover, these negotiations depended on time-invariant characteristics that are captured by our district-level

[16] Only few districts become producers during the period of analysis. Eliminating them from our sample does not change our results (results available upon request).

fixed effects and thus, they provide further support to our identification approach. Holding the investment capacity of the local governments constant, by the use of district fixed effects, we explore whether the year-to-year variation in the amount of transfers and mining production helps in the formation of human capital measured by test scores.

Finally, unobservable factors may affect both mining production (and therefore fiscal redistribution) as well as the educational outcomes if for instance local demand and labor market conditions are correlated with the mining production. However, by controlling for the value of mining production we address this concern insofar as observed production is the result of a market equilibrium. On top of this, we perform robustness tests later on excluding producing districts and their neighbors –whom are arguably subject to spillovers from producing districts—and still find evidence in support of our argument.

Our identification strategy differs but complements other approaches in the empirical literature on the effects of resource booms. For example, Dube and Vargas (2013), using the case of Colombia, exploits exogenous variation in international prices of oil to instrument endogenous value of production. Their strategy exploits variation for the case of producer districts in settings where the allocation of natural resource rents are granted exclusively to these type of districts.[17] As discussed above, in our setting producer districts are granted only the 10% of the total amount of *Canon* transfers generated, the rest being allocated to other districts in the province and the region (including a fraction assigned to the regional governments and regional universities). Hence looking at the effect of mining production on test scores will certainly leave aside a relevant part of the variation we want to understand.

5. Results

5.1. Effect of *Canon* transfers

We start by consider the effect of the *Canon* transfers on test scores. Table 2 displays our estimates. In Panel A we focus on math and Panel B on reading. We start with a simple model using a linear specification for *Canon* transfers and ignoring the role of mining production but incorporating all the fixed effects from Equation (1). For math, panel A, we find a positive

[17] This was certainly the case for Colombia before 2011, before the royalty system was modified. See Gallego et al. (2020) for a discussion about the Colombian royalty system and the effects of the reform.

association in this simplest model (column 1) but it is not statistically different from zero. However, a quadratic functional form suggests a nonlinear link (column 2). This pattern is consistent with the non-monotonic effects of resource booms highlighted by the political economy literature described earlier. The effects for reading are much smaller and are not statistically different from zero (Panel B).[18]

Adding controls for the value of mining production (column 3) as well as student and school characteristics (column 4) does not alter our findings: there are positive, statistically significant (but marginally decreasing) effects for math, and negligible impacts for reading. Consistent with our previous analysis, the coefficient for mining production is not statistically significant after controlling for *Canon* and its square. The lack of significance for mining production after controlling for *Canon* transfers suggests that the market-based channels of a resource boom seem to be irrelevant in our setting.

Table 2. Effects of *Canon* on academic achievement

	Dependent variable: Test scores				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Panel A. Math scores				
Canon	7.2844	22.8601**	23.0187**	25.1328***	22.5513**
	(4.6782)	(9.5349)	(9.6193)	(9.4648)	(9.4570)
Canon squared		-2.0713**	-2.0797**	-2.2729***	-2.0215**
		(0.8379)	(0.8408)	(0.8257)	(0.7853)
Mining production			-0.0222	-0.0111	-0.0364
			(0.0453)	(0.0422)	(0.0452)
Canon (lag)					-2.0750
					(6.4640)
Canon squared (lag)					0.3651
					(0.6222)

[18] We are not the first in finding impacts on math scores but no effects on reading scores. The existence of effects on one subject but not in the other have been documented for interventions such as school vouchers (Shakeel et al, 2016), school feeding programs (Lawson, 2013) and other educational interventions (Evans and Popova, 2016). Even the effects of climate change on learning show a differential impact between math (negative) and reading (no effect) as suggested by Graff Zivin et al (2018). The lack of effects on reading scores has been interpreted as evidence of household complementarities in learning, especially for primary schools because parents and older siblings can support students' learning process due to the lack of complexity of the subject (Shah, 2017). This does not occur in the case of math given that it requires more specialized knowledge. This has led to the development of innovations designed to help parents to engage in their children math learning, but only evidence for of U.S. is available (Berkowitz et al., 2015).

Mining production (lag)					-0.0325
					(0.0204)
R-squared	0.1506	0.1507	0.1507	0.1604	0.0063
Number of students	2072351	2072351	2072351	2012798	2072351
			Panel B. Reading scores		
Canon	-0.3903	-2.0187	-2.0558	-2.4656	-2.7579
	(1.7511)	(4.3111)	(4.3462)	(4.4867)	(4.3115)
Canon squared		0.2164	0.2184	0.2335	0.2444
		(0.3718)	(0.3728)	(0.3835)	(0.3528)
Mining production			0.0052	0.0154	0.0004
			(0.0257)	(0.0231)	(0.0298)
Canon (lag)					-0.5900
					(4.0008)
Canon squared (lag)					0.1118
					(0.3789)
Mining production (lag)					0.0112
					(0.0127)
R-squared	0.2598	0.2598	0.2598	0.2895	0.0266
Number of students	2068281	2068281	2068281	2008941	2068281
Student controls	N	N	N	Y	N
School controls	N	N	N	Y	N

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Mining and *Canon* correspond to the value of mining production per-capita and *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include fixed effects at the district level and by year. School characteristics include: school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include: gender and mother language (Spanish/other) of the children.
Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Considering column 4, where all controls are included, the test-score-maximizing amount of *Canon* is about US$ 5,500 per capita per year. Figure A3 in the Appendix reports the marginal effect for this specification. Conditional of receiving a transfer, the 99-percentile value of *Canon* transfers is only US$ 740 per capita. Thus, for nearly all districts receiving *Canon*, our findings suggest a positive effect of the transfers on math test scores. Moreover, given that the average transfer during the period of our analysis is US$ 70 per capita for the sample of districts that received strictly positive transfers, our estimates suggest an increase of around 24 percent of a standard deviation in math scores at this point of the distribution.[19]

To put our results in perspective, the average impact of the *Canon* on test scores is higher than 83 percent of the studies reported by Kremer et al. (2013) who analyze primary school interventions evaluated with randomized control trials. For example, based on the authors' review, our effect is larger than all the studies where "business as usual" resources are provided (e.g., textbook, class size, flipcharts) and all but two of the pedagogical innovations.

5.2. Robustness checks

5.2.1. Robustness to influential observations

We explore whether our findings are driven by extreme values of *Canon*. To identify these observations, we use the standard Cook's distance, Welsch Distance and difference in fits (DFITS) procedures. This comprised about 5% of observations when performing the DFITS and Cook's distance procedures, and about 2% for the Welsch distance procedure. Our results are robust to removing these observations (see Appendix Table A2).[20] Note that in the context of the resource curse literature, administrative units with extremely high values of natural resource rents are of particular interest. For our study, large *Canon* values are not "anomalous values" arising from problems like measurement error given that these come from official administrative data on transfers to districts. Instead, these large values are important empirically as we seek to test a theory predicting that we should observe a resource curse for large transfers.[21]

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[19] Our results are robust to an additional standardization of test scores in the form of a z-score using the mean and standard deviations from 2007. Table A1 in the Appendix shows these results and Table A16 for the heterogenous effects.

[20] Figure A5 in the Appendix plots the partial regression lines associated with the first- and second-order effects of the value of *Canon* on math test scores. Consistent with our main findings, the first-order effect is positive, and the second-order effect is negative, with tight 95 percent confidence bands. The panels of the figure illustrate that the result is robust to different specifications of the residuals.

[21] We also consider whether our results are affected by transforming the *Canon* transfers using natural log (plus one), box-cox and inverse hyperbolic sine. However, as shown in Appendix Figure A4, these transformations do not change the shape of the empirical distribution because there are many districts whose local governments do not receive canon transfers while a relatively small fraction of them receiving large levels of transfers. Therefore, regressions using this transformation do not alter our main finding (available upon request).

5.2.2. Lagged model

Our main specification does not include *Canon* lags. Indeed, there is evidence suggesting that mayors react immediately to the transfers because not doing so could lead to higher political competition and higher likelihood that the central government will reduce transfers due to low budget execution (e.g., Maldonado, 2020; Maldonado and Ardanaz, 2020). Furthermore, in the case of mining production, previous studies have shown that the effect on market outcomes is contemporaneous (Jacobsen and Parker, 2014).[22]

Also, we argue that it is quite common to find contemporaneous effects of educational interventions on test scores. McEwan (2015) reviews 77 randomized controlled experiments focusing on primary school interventions in developing countries. He finds that in all but seven studies, the evaluation was conducted at the end of the academic year when the intervention started. This review is very important for our study because it focuses on children in primary school while our analysis centers on second graders. Thus, our findings of contemporaneous effects among second graders in Peru, are in line with the vast literature evaluating school learning in developing countries.

Nonetheless, in this sub-section we expand the model to test whether lagged values of the *Canon* matter. In our setting, we only have test score data for second graders, so *Canon* at $t-1$ explores the role of transfers when students were in first grade.[23] Grade repetition is not an issue here because, by law, children cannot repeat first grade in Peru. In Table 2, column 5, we present the results of including $t-1$ in the *Canon* transfers (and its square). Such addition does not change our previous findings and show that lagged values play no role on test scores. This evidence reinforces the theoretical arguments and therefore we conduct the rest of the analysis with *Canon* values at t as our main specification.[24]

5.2.3. Relaxing the parametric quadratic specification

[22] On top of this recent theoretical scholarship has shown that lag identification requires stronger and implausible identification assumptions. For instance, Bellemare et al. (2017) have shown that using lags would require strong assumptions regarding the dynamics of unobservables. Even more concerning are results obtained from Monte Carlo simulations that provide evidence that lags could worsen identification and the quality of inference in such a way that it is often better just to ignore endogeneity issues altogether (see Bellemare et al, 2017, for details).

[23] Lags beyond t-1 would make little sense when considering second graders. For example, $t-2$ implies evaluating the effects on transfers to schools before children entered first grade. Therefore, we limit our analysis to $t-1$.

[24] We also consider the lagged model when we explore heterogenous effects and continue to find only a contemporaneous effect. See Appendix Table A5.

The non-monotonic effects of mining *Canon* on learning outcomes are consistent with the political economy arguments discussed earlier but they strongly rely on the use a quadratic parametric approximation. To evaluate whether this approach is consistent with the data, we extend the empirical model to include other polynomials and check whether they offer a better fit.

Table A3-A in the Appendix presents the results of the analysis. Columns 1 to 3 replicate the results for the basic specification while we add cubic and quartic terms for mining *Canon* in columns 4 and 5. As a benchmark, we first test whether the coefficients for the quadratic approximation are both equal to zero. We confidently reject the null hypothesis that both coefficients are equal to zero (F-statistic of 3.08 with a p-value of 0.05) for the case of math scores. For the case of the cubic and quadratic approximations, we implement a test for nested models in which the null hypothesis assumes that the quadratic approximation offers a better fit compared to alternative specifications. In both cases, we fail to reject the null: F-statistic of 0.33 with a p-value of 0.56 against the cubic specification and F-statistic of 0.24 with a p-value of 0.78 against the quartic model. Therefore, the evidence suggests that the quadratic approximation offers the best fit to the data. Similar results are obtained for reading (Panel B).

One related concern is that this estimated non-monotonic relationship is driven by a particular type of student, for example those that overperform or underperform in the standardized test. Therefore, it is possible that our main results are not robust to this issue. To address this concern, we implement the fixed effects quantile regression model proposed by Machado and Santos Silva (2019). As it is well known, although it weights the errors in a different way, quantile regression is robust to a potential problem with outliers in the conditional distribution of the outcome (Koenker, 2005).

Table A3-B in the Appendix presents results from the proposed approach. The results for the median regression (quantile=0.5) are, incidentally, close to the mean effects estimated in Table 2. Remarkably, all the estimates for the quantiles 0.1 to 0.9 show robust evidence in favor of the non-monotonic relationship highlighted by our conceptual framework.

5.2.4. Alternative samples of districts according to mining production

One possible concern is that endogenous production responses may play a role even after controlling by mining production in the econometric specifications. To address this issue, we take advantage of the fact that the mining *Canon* Law establishes that non-producer districts located in a producing province also receive a fraction of the rent generated by mining exploitation. This allows us to test the impact of the redistribution of natural resource rents in settings where production externalities and possible production endogenous responses are not expected to play a role.

For this purpose, we limit the sample to non-producing districts located in producing provinces. Table A4.1 in the Appendix presents the results. The coefficients are statistically significant and larger than those reported in Table 2 for the basic specification on math test scores (Panel A, columns 1 and 2). This result is robust to controlling for student and school characteristics (column 3). In Table A4.2, we exclude districts that share a boundary with producing districts. We still find the same effect: a non-linear relationship between *Canon* transfers and test scores. As before, there is no effect for the case of reading scores (Panel B of Table A4.1 and A4.2).

5.2.5. Permutation tests

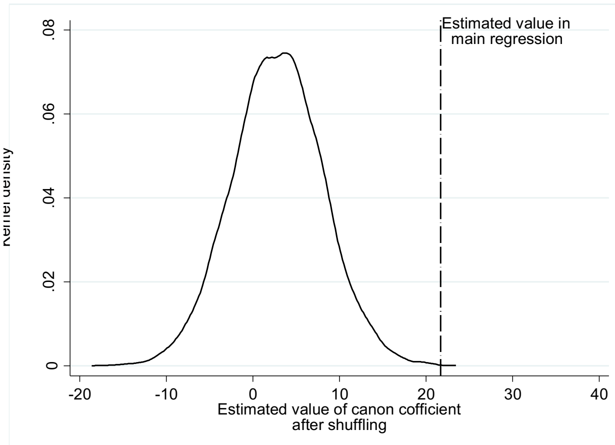
To further validate our empirical strategy, we consider falsification tests by incorrectly assigning the time series of *Canon* transfers and mining production, $\{c_{dt}, m_{dt}\}$, that belong to district d to a randomly chosen district j from the set of all districts in the country. If unobserved characteristics, beyond the ones controlled with the district and year fixed-effects, are behind our findings for the *Canon* transfers, we should expect this permutation exercise to produce non-zero impacts.[25] In Figure 3, we show the distributions for the linear and quadratic coefficients from 10,000 permutations, after controlling for mining production. This is the same specification used in Table 2, column (3), whose benchmark parameter is reproduced here as the vertical dashed lines to ease the comparison. As expected, in Panels A (linear) and B (quadratic) we clearly observe that the incorrect assignment of *Canon* transfers produces estimates centered around zero (no effect). The original estimates are far away from these non-zero effects and they are unlikely to be generated by this (incorrect) random assignment given the shape of the density function. These

[25] The use of permutation tests as a robustness check is not rare in the empirical literature. See, for instance, Abadie et al (2008) for an application of a similar spirit of the one used in our paper.

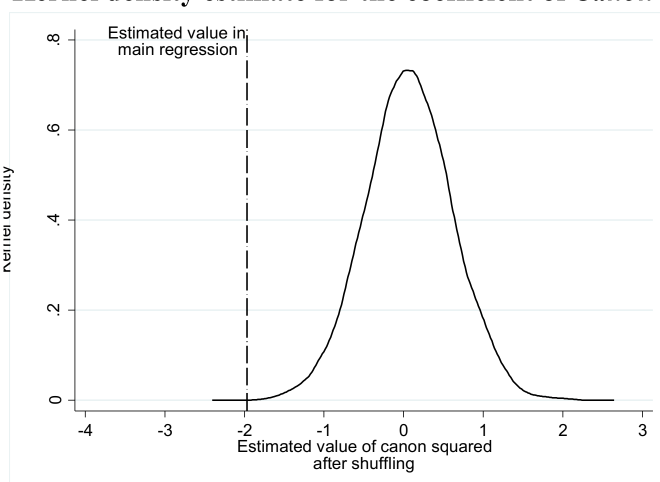
results provide further evidence of the validity of the identifying assumptions for our empirical strategy.[26]

Figure 3. Canon transfers permutation tests

A. Kernel density estimate for the coefficient of *Canon*



B. Kernel density estimate for the coefficient of *Canon* squared



Bandwidth: 0.2

Note: In the corresponding regressions, *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. The regressions do not include school characteristics or student characteristics.

[26] Note that the nature of the *Canon* transfers makes it impossible to obtain valid inference if this incorrect random assignment is done when *j* is obtained from the region or province where *d* is located. As described in Section 2, districts in the same province or region of a producing district will receive a transfer that is correlated with the one received by district *d*. Thus, transfers to *d* and its neighboring districts are not spurious as is the case where *j* is drawn from any district in the country. In the Appendix, Figure A6, we show that when such permutations are done, the distribution of the incorrect permutations is not centered around zero. However, our point estimates are still located in low-probability regions for these distributions.

Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

5.3. Heterogeneous effects

In Table 3 we report regressions exploring heterogeneous effects regarding the public-private and urban-rural divides. In column (1) we reproduce the results for the entire sample to ease comparisons. The quadratic relationship in mathematics is present in all subsamples except for private schools (column 5). This result is consistent with the fact that mining production has very limited impact on local economic conditions, otherwise the effects would be noticed on children attending private schools too. These findings provide additional support to the hypothesis that the main driver factor is political since Peruvian mayors seem to use mining *Canon* funds to improve learning conditions in public schools only. We will provide additional evidence on this regard in the next section. Also, in columns (6) and (7) we show that effects are the same when dividing the sample by gender: in both cases we continue to find non-linear effects of the *Canon* for math and no impact for reading.[27]

[27] These results are robust to the exclusion of influential observations (Tables A6-A to A6-C in the Appendix).

Table 3. Heterogeneous effects of *Canon* on academic achievement

	All	Urban	Rural	Private	Public	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. Math scores			
Canon	25.1328***	26.2588**	21.7433**	-4.9008	27.0129***	28.5620***	21.8927**
	(9.4648)	(11.3043)	(9.8586)	(16.6186)	(9.2414)	(10.4155)	(9.0555)
***Canon* squared**	-2.2729***	-2.3552**	-2.1770**	-0.1002	-2.4098***	-2.5609***	-1.9908**
	(0.8257)	(0.9809)	(0.8555)	(1.2529)	(0.8626)	(0.9171)	(0.7864)
R-squared	0.1604	0.1472	0.1278	0.0986	0.1519	0.1582	0.1646
Number of students	2012798	1353896	653410	299441	1713357	987444	1025354
				Panel B. Reading scores			
Canon	-2.4656	0.6823	0.9681	-24.7742**	1.7615	-2.0640	-2.8719
	(4.4867)	(4.6661)	(7.4444)	(9.8061)	(4.5665)	(4.5879)	(4.8169)
***Canon* squared**	0.2335	-0.0805	-0.0391	2.0427***	-0.2218	0.0516	0.4126
	(0.3835)	(0.3959)	(0.6528)	(0.7328)	(0.4063)	(0.3903)	(0.4129)
R-squared	0.2895	0.2303	0.1693	0.1505	0.2483	0.3054	0.2751
Number of students	2008941	1351621	651838	299302	1709639	985751	1023190

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

5.4. Mechanisms

We now explore several mechanisms that could explain how the *Canon* transfers increase academic performance, as measured by test scores. We do this by using the same identification strategy as before but replacing the test scores outcomes in Equation (1) with new outcomes at the district, school and household level, depending on the dataset.

We start by testing whether transfers increase local government's expenditures on education and cultural items. Based on the theoretical models of political economy discussed earlier, we expect this expenditure to increase with transfers to local governments but to exhibit diminishing marginal returns, because at higher rent levels incumbents would invest less on public goods. In Table 4, column 1, using data at the district level, we find evidence in support of such models. These results expand the findings from Caselli and Michaels (2013), who show that oil windfalls in Brazil increase local-government education expenditure. Also, in Brazil, but in the late 1980s, Litschig and Morrison (2013) find a positive effect on local expenditure on education from intergovernmental transfers. These papers, however, did not explore, non-linear specifications making our findings an important contribution.

We expand our set of outcomes to explore whether *Canon* transfers created improvements in school infrastructure and the quality of teachers for the subset of public schools. Specifically, we use data from the Censo Escolar and test if variation in *Canon* transfers relates to the hiring of teachers with long-term contracts (columns 4), percentage of teachers with college degrees in education (columns 5) and basic infrastructure services in the school: electricity (column 6), water (column 7) and sanitation (column 8).

Table 4. Mechanisms: Local government expenditure and school-level characteristics

	Dependent Variables							
	All		Public schools only					
	Log of Local govern-ment expenditu-re in education and culture	School enroll-ment	School enroll-ment	Percentage of teachers with long-term contract (at the school level)	Percentage of teachers with a tertiary education degree in a school teaching program	School has access to electricity	School has access to water	School has access to sanitation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Canon	0.0755*** (0.0272)	0.0116 (0.0084)	-0.0082 (0.0183)	-0.0021 (0.0300)	0.0020 (0.0061)	0.1323*** (0.0388)	0.0533* (0.0309)	0.1606*** (0.0480)
***Canon* squared**	-0.0093** (0.0044)	-0.0011 (0.0008)	0.0005 (0.0015)	-0.0014 (0.0022)	0.0001 (0.0005)	-0.0086*** (0.0033)	-0.0032 (0.0025)	-0.0116*** (0.0042)
R-squared	0.4607	0.1560	0.1645	0.3251	0.1242	0.3481	0.3319	0.3858
Number of districts	9947							
Number of schools		237541	98820	82449	82449	92463	92459	92449

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

We find that the *Canon* is non-linearly and statistically significantly associated with improvements in the access to electricity and sanitation.[29] As further shown in the Appendix, Tables A7 and A8, these effects are indeed concentrated on public schools and schools in rural areas. These findings also speak to the large literature about the role of resources on education outcomes (e.g., Hanushek, 2006; Glewwe and Kremer, 2006; Glewwe and Muralidharan, 2016; Jackson, 2018). In this sense, we also complement the work by Ferraz et al. (2012), who find that corruption has a negative effect on students' academic performance in Brazil as politicians deviate resources away from education.

In columns (2) and (3) of Table 4 we rule out the possibility that population effects drive improvements in test scores. We find no effect on school enrollment from *Canon* transfers, suggesting that larger windfalls did not seem to attract families with children.[30] This is consistent with the work of Aragón and Rud (2013) who focused on Yanacocha, a large gold mine in Northern Peru. The authors also find no changes in the composition of the labor force—measured by education, gender and portfolio of crops—using a difference-in-difference approach.

Yet, Loayza and Rigolini (2016), using the 2007 Peruvian population census, find that areas with mining booms attracted skilled migrants. Our results showing no effect on school enrollment could still be consistent with the Loayza and Rigolini's findings, if migrants are not coming with their families. Such migration pattern would be consistent with a household division of labor aimed at maximizing earnings from work opportunities (e.g., Chant, 1991; Hugo, 2003, 2006). Also, Loayza and Rigolini's analysis uses only data from 2007, which is the starting of our period of analysis. Thus, if skilled migration were temporary, circular, or concentrated at the beginning of the boom, our results would also be consistent with theirs. Furthermore, they base their empirical design on a cross-sectional variation that does not necessarily allow them to account for unobserved factors related to both, migration and mining production or *Canon* transfers. We base our design, in contrast, on a method that voids such a possibility. Thus, our different research strategy could also explain these different findings.

[29] According to the current legal framework, local governments' responsibilities can be classified in exclusive and shared with other government levels. The shared functions include participation in management of school services, public health, culture, sports and recreation, citizen security, transport, housing, and social programs and waste management. Although local governments do not hold the full responsibility of managing schools, they do participate in supporting schools under their jurisdiction.

[30] Consistent with our previous results, we find no impact on enrollment for the case of public schools. However, we do find a non-monotonic effect in enrollment for the case of private schools.

We now use household-level data from ENAHO to investigate whether changes in health outcomes as additional potential mechanisms. Our analysis complements previous findings exploring the impacts of production and *Canon* on consumption and poverty using census data (Loayza and Rigolini, 2016), household surveys (Aragón and Rud, 2013) or both (Zambrano et al, 2014).

For Table 5 we merge the ENAHO household surveys from 2007 to 2012 with the *Canon* and mining datasets. We test whether the *Canon* improves health conditions of adults and children (aged 6-10). As discussed by Litschig and Morrison (2013), investigating the impact of intergovernmental transfers on health outcomes is a natural step when understanding whether such transfers could improve human capital. In Table 5 we consider three (self-reported) indicators: having health complications in the last four weeks, whether the individual felt sick in the last four weeks and the number of days an individual between 15 and 64 years of age that could not work due to being sick. Our results indicate that *Canon* transfers are associated with health improvements. We observe a decline in the probability of experiencing health complications for adults and children (columns 1 and 2), as well as a decline in the probability of being sick recently (but for adults only, column 3). The results are essentially the same for urban and rural areas (Table A9 in the Appendix), although it seems we lack statistical power for that analysis.

We also evaluate whether *Canon* transfers, through the expansion of the public education budget, created a crowding-out effect on household's education expenditures.[31] We do not find evidence of crowding-out at the household level, suggesting that parents do not see their inputs as substitutes with respect to school-based inputs.[32] Finally, we show that these results are robust to the exclusion of influential observations as discussed in section 5.2.1. This exercise is presented in Appendix Table A10 and A11.[33]

[31] See Litschig and Morrison (2013) for a discussion of the "flypaper effect" and crowding out on own revenue and other revenue sources among local governments in the presence of intergovernmental transfers.
[32] We evaluate the non-monotonic effect of *Canon* on household spending on education per-student living at home using data from ENAHO, finding no evidence of a statistically significant effect of *Canon* on the latter. These results are available upon request.
[33] We also explored the robustness to the inclusion of lagged variables. See Appendix Tables A12 and A13.

Table 5. Mechanisms: Role of health factors

	Dependent variable				
	Individual experienced health complications in the past 4 weeks		Individual was sick in the past 4 weeks		Number of days individual couldn't work due to sickness in the past 4 weeks
	(All individuals)	(6 to 10 years of age)	(All individuals)	(6 to 10 years of age)	(14 - 65 years of age)
Canon	-0.0956***	-0.0637	-0.0621**	-0.0776*	0.0067
	(0.0281)	(0.0543)	(0.0291)	(0.0468)	(0.0522)
***Canon* squared**	0.0096***	0.0105**	0.0050**	0.0077*	-0.0026
	(0.0023)	(0.0044)	(0.0023)	(0.0040)	(0.0041)
Observable characteristics	No	No	No	No	No
R-squared	0.0693	0.0558	0.0347	0.0568	0.0137
Number of observations	450615	49606	450615	49606	370499

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010.
Source: Authors' calculations based on ENAHO household survey and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

6. Conclusions

We study whether booms of natural resources affect human capital accumulation, exploiting a natural experiment in the mining sector of Peru, a country with low governance indicators. We find non-monotonic effects of the redistribution of mining rents on math scores, but no effect for the case of reading. The former is positive and large: 0.24 standard deviations for the average municipality, implying that the mining boom in Peru has been beneficial for students in almost all recipient localities. The net effect is negative only for extremely *Canon*-rich municipalities (top 1% in terms of mining *Canon* distribution). These results are in line with recent scholarship documenting non-monotonic and perverse effects for natural resource-rich regions. This evidence is also consistent with a political economy argument where mayors invest in public goods when they expect to keep power but underinvest when they face more political competition. In fact, we find that these effects are mainly driven by public schools and by changes in school-level conditions such as infrastructure. These are ways in which incumbents can invest mining *Canon* transfers.

We find evidence that the redistribution fueled by the resource boom had non-monotonic effects for health outcomes too. These results can be a consequence of improvements in the quality and access to health facilities, something that has been documented in other studies (Maldonado and Ardanaz 2020; Maldonado 2020).

The evidence presented in this paper puts into question some beliefs in the literature about the role of natural resources in development. Recent studies have emphasized that natural resources can be a "blessing" only when good institutions are available. However, we have shown that a natural resource boom can lead to an increase of human capital accumulation in a context of poor institutions, but only when mechanisms of distribution of natural resource windfalls are in place.

Moreover, we find that only very *Canon*-rich municipalities experience negative effects of a resource boom. This may explain the anecdotal evidence of the resource curse literature, typically motivated by highlighting the economic and political distortions experienced by extreme natural wealth in the Middle East or Africa. Thus, natural resources can lead to a curse only for extremely natural resource-rich societies, and it can potentially be a blessing for some others.

Undoubtedly, the effect of natural resource booms on academic achievement deserves further research, in particular under different institutional set-ups and windfalls-redistribution schemes. Focusing on the Peruvian case, perhaps one important question that remains open for discussion is: What are the long-term effects of mining production on the social outcomes analyzed herein once the boom ends? Jacobsen and Parker (2014) find long-lived negative effects in the labor markets after the end of the 1970s gas and oil bonanza in the United States. However, we have not seen evidence documenting the long-run effects on human capital formation after the bust.

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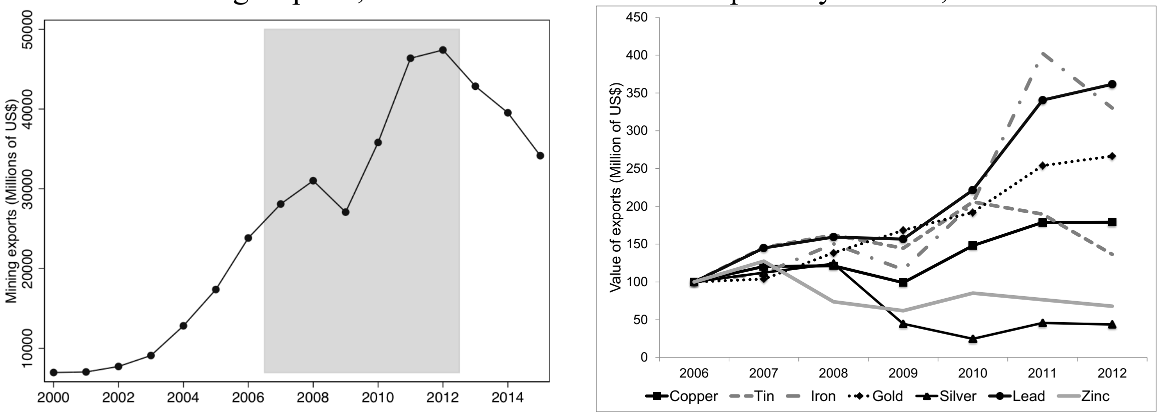
Online Appendix – Not for Publication

Figure A1. Trends in Mining Exports

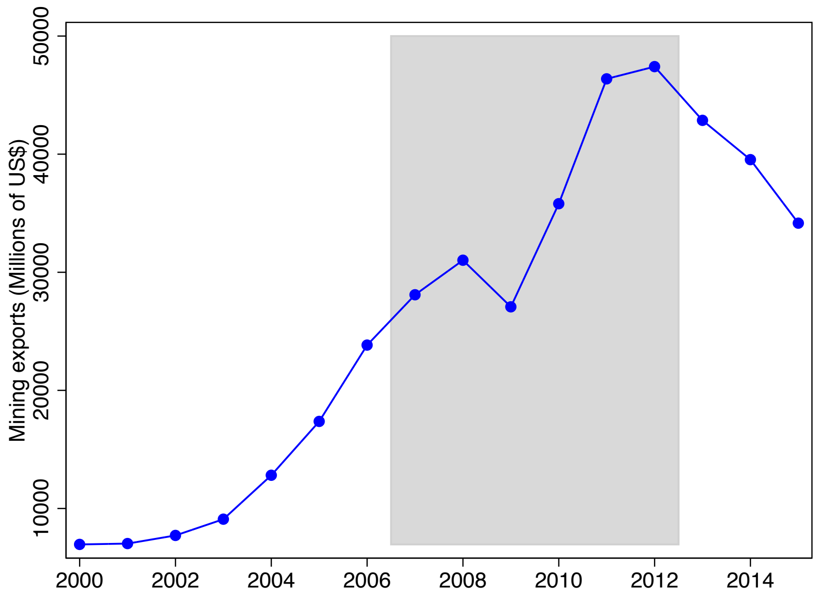
A. Total Mining Exports, 2000-2015 B. Exports by mineral, 2006-2012



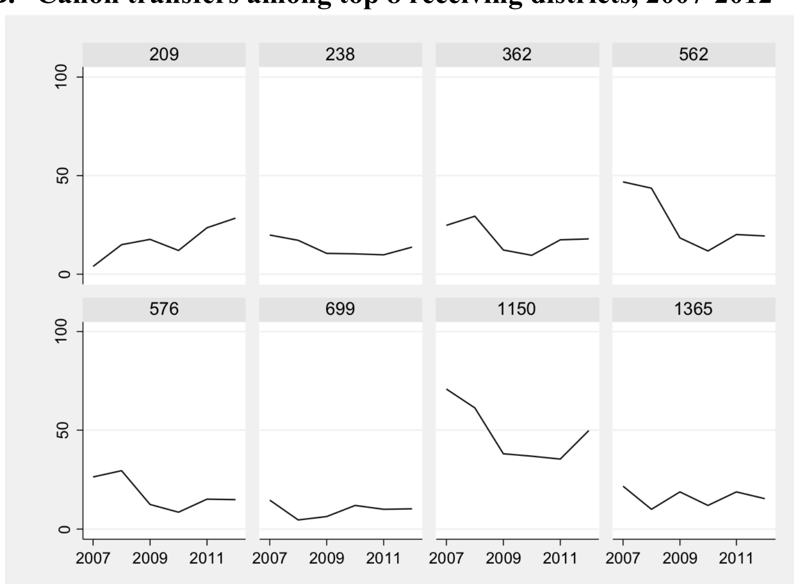
Note: Shaded area (Panel A) indicates the period of analysis (2007-2012). Data for this graph can downloaded from http://www.bcrp.gob.pe/.

Figure A2. Trends in *Canon* transfers

A. Total *Canon* transfers: 2000-2015



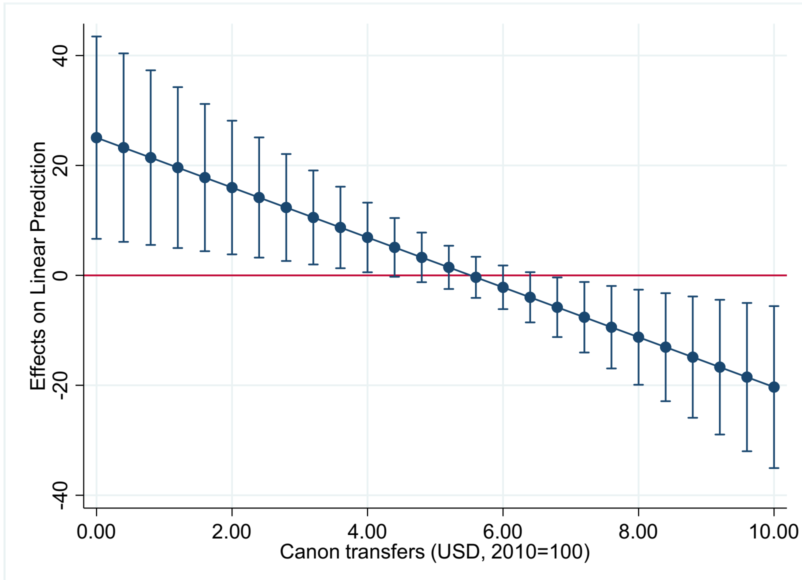
B. Canon transfers among top 8 receiving districts, 2007-2012



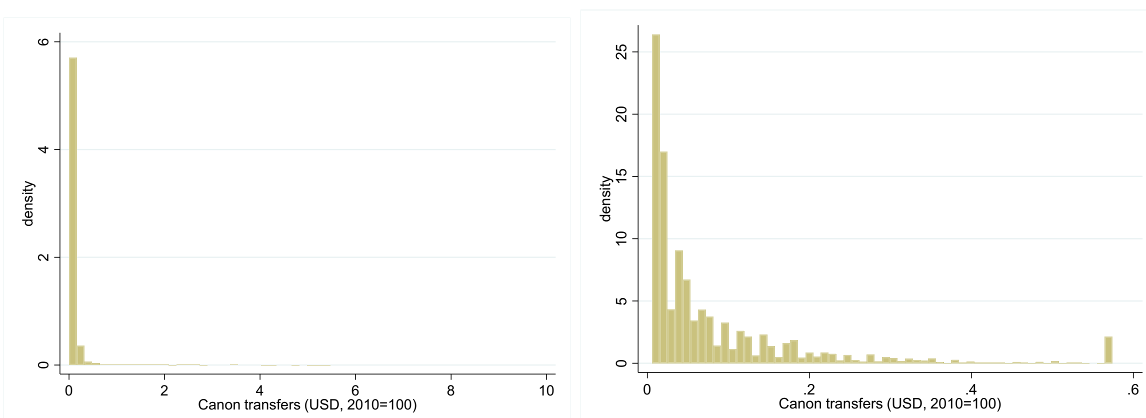
Note: Shaded area (top figure) indicates the period of analysis (2007-2012).
Source: Authors' calculation based on data from Peru's Ministry of Finance.

Figure A3. Heterogenous effect of *Canon* transfers

a. Predicted marginal effect along the support of *Canon* transfers



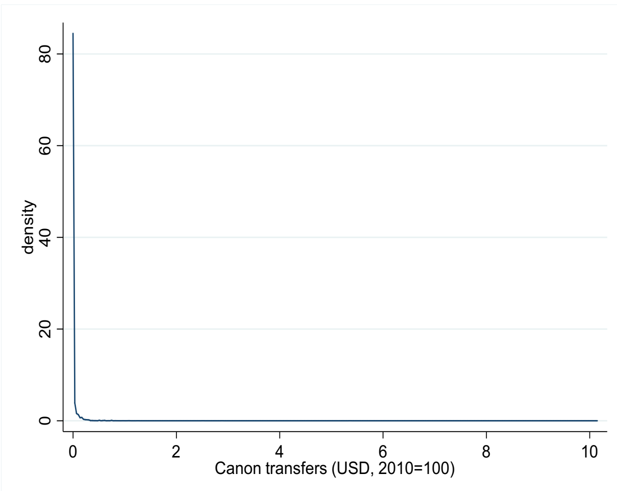
b. Distribution of observations along the support of *Canon* transfers



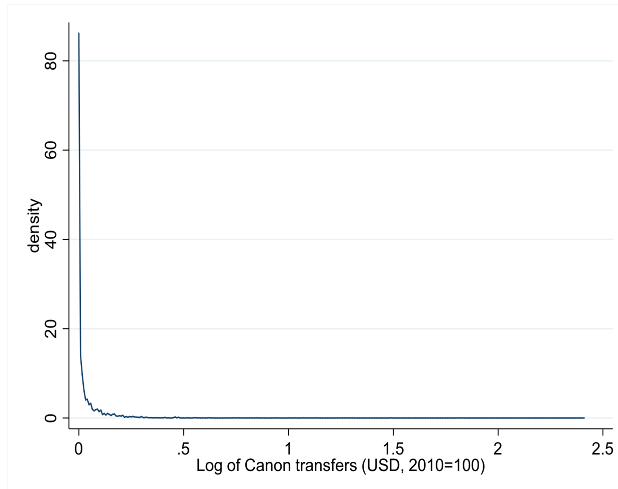
Note: Panel A reports the distribution of *Canon* transfers for the full support of the *Canon* distribution (right) and the corresponding distribution excluding the 99th percentile (left). In Panel B, we include 95% confidence intervals for the point estimates. In the corresponding regressions, mining and *Canon* correspond to the value of mining production per-capita and *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include fixed effects at the district level and school characteristics and student characteristics.
Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Figure A4. Kernel density distribution of observations along the support of Canon transfers for different transformations of the Canon variable

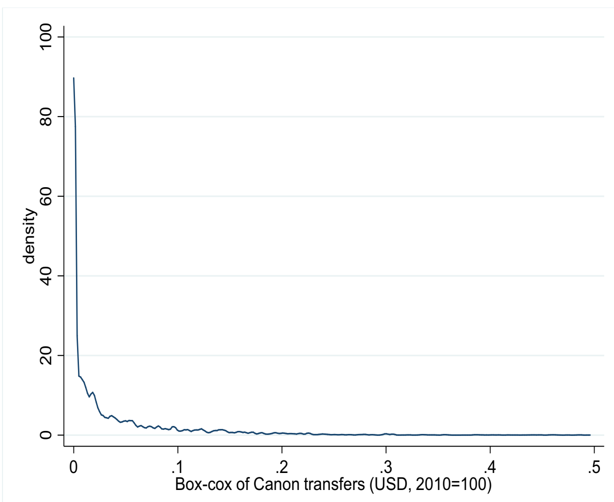
A. Canon in levels



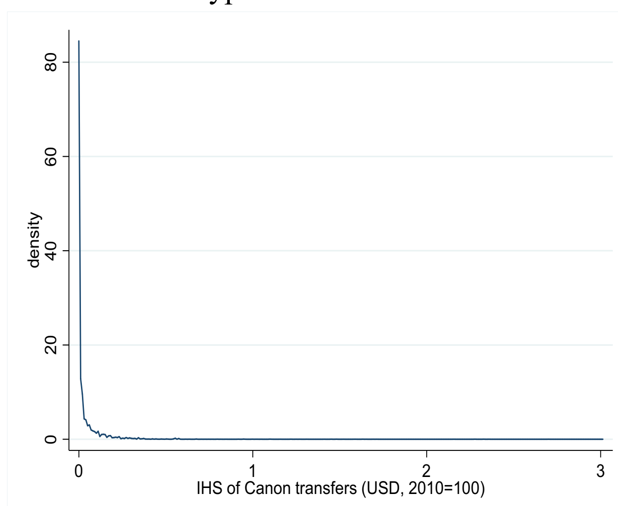
B. Log(Canon+1)



B. Box-cox transformation, $\widehat{\lambda} = -2$



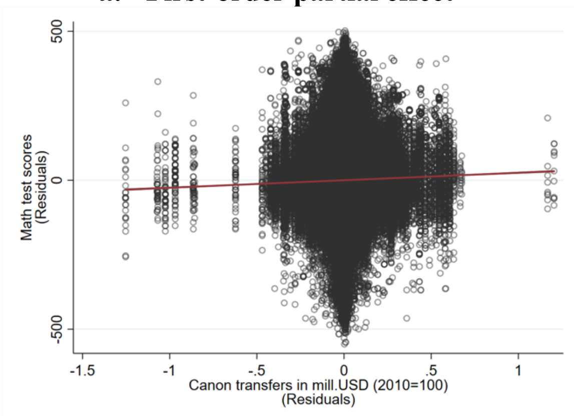
C. Inverse Hyperbolic Sine transformation



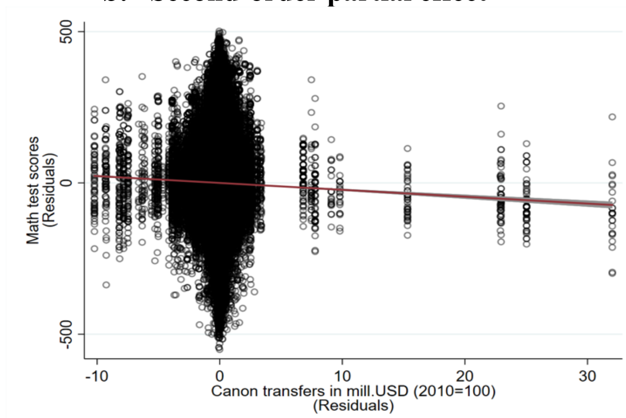
Note: IHS stands for Inverse Hyperbolic Sine. For the Box-Cox transformation, we estimate the “optimal value” of λ for which the transformation results in the best approximation to a normal distribution. We obtained that $\widehat{\lambda} = -2$.
Source: Authors’ calculations based on data from Peru’s Ministry of Education, of Finance, of Energy and Mines, and INEI

Figure A5. First- and second-order partial effects

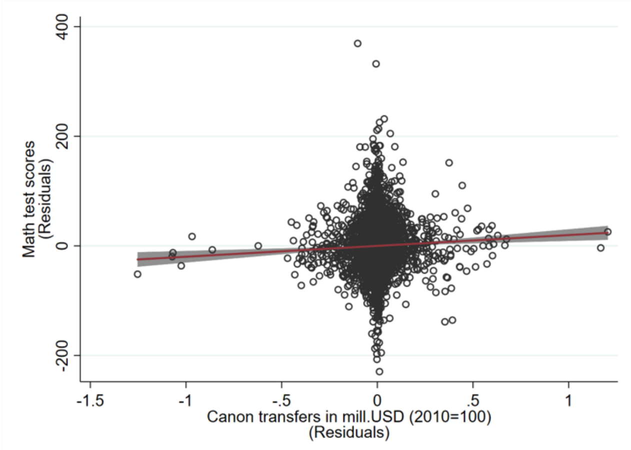
a. First-order partial effect



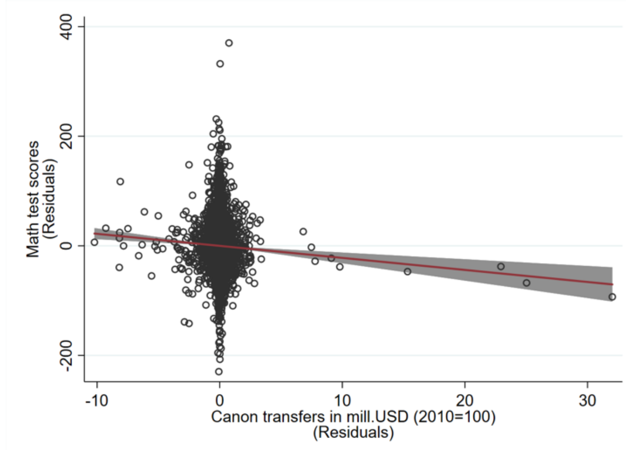
b. Second-order partial effect



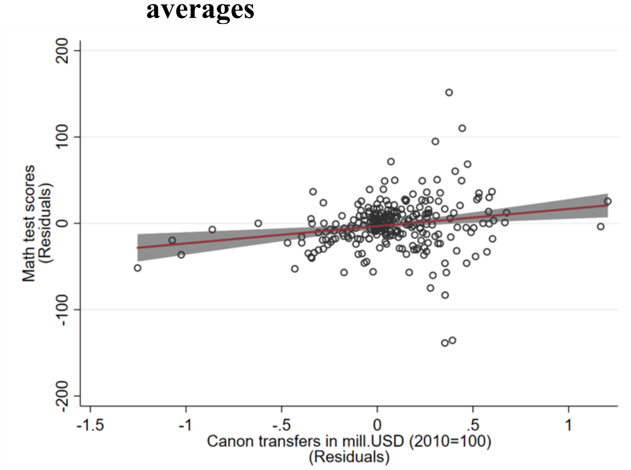
c. First-order partial effect, district averages



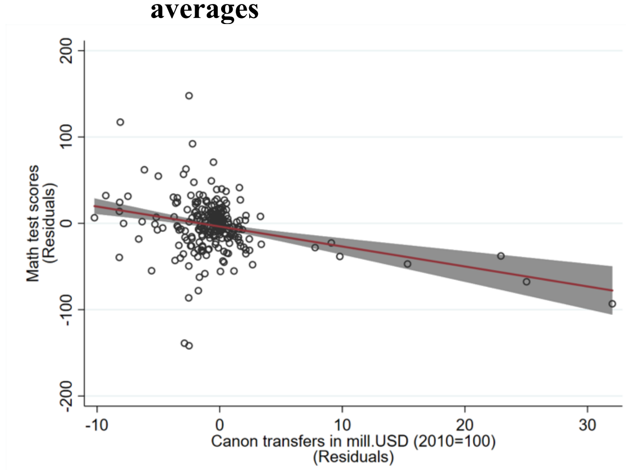
d. Second-order partial effect, district averages



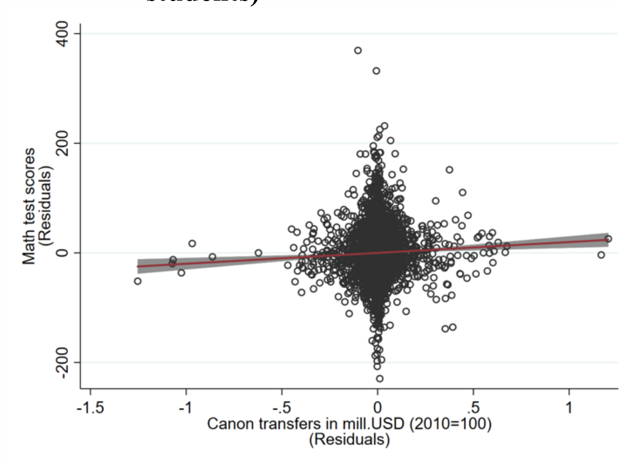
e. First-order partial effect, binned averages



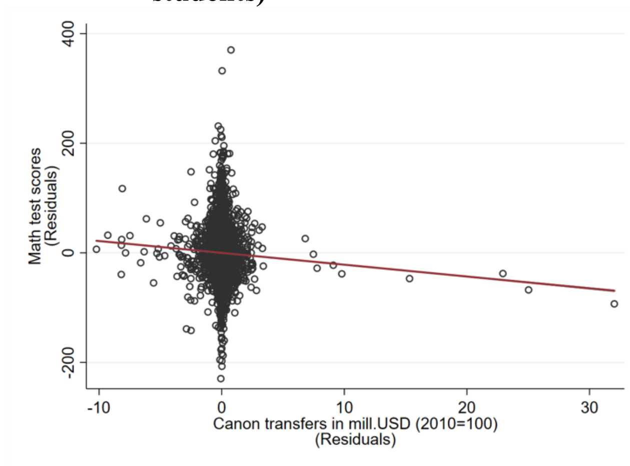
f. Second-order partial effect, binned averages



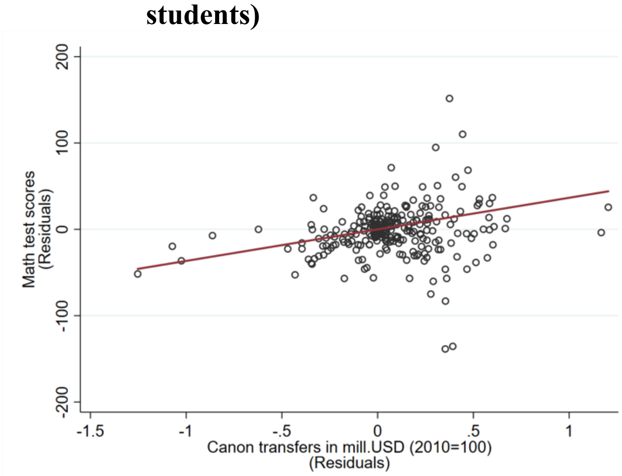
g. First-order partial effect, district averages (weighted by number of students)



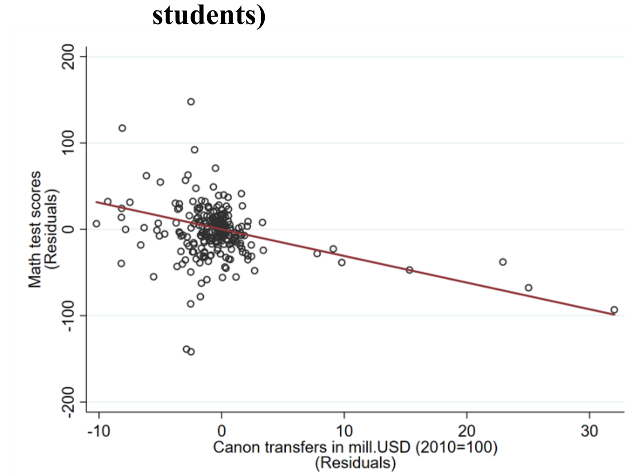
h. Second-order partial effect, district averages (weighted by number of students)



i. First-order partial effect, binned averages (weighted by number of students)



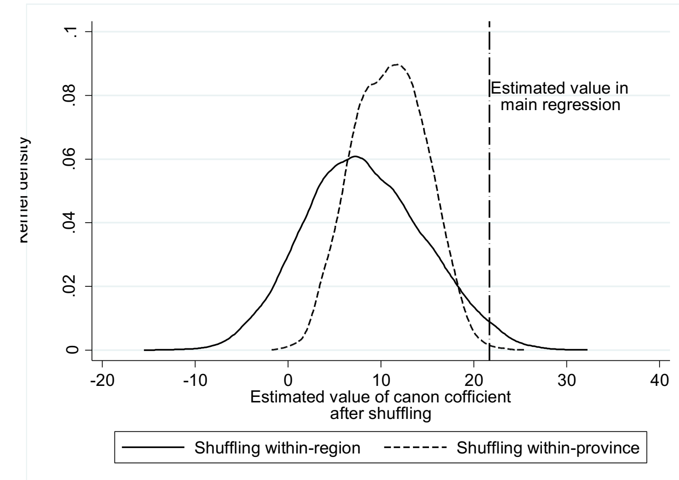
j. First-order partial effect, binned averages (weighted by number of students)



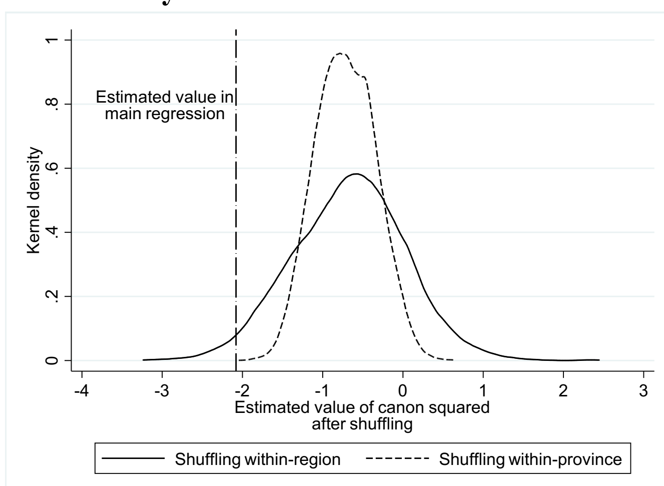
Note: Left panels (A, C, E, G and I) depict the first-order partial effect, and right panels (B, D, F, H and J) show the second-order partial effect, of canon on math test scores, conditional on production and the district type (i.e., dummies of producer, non-producer in producing province), student and school characteristics, and time and district fixed effects, against the value of canon transfers. Each panel shows a plot of residuals against residuals. The x- and y-axes in A, C, E, G and I plot the residuals obtained from regressing the linear term in canon and math test scores, respectively, on the quadratic term in canon as well as the aforementioned set of covariates. Conversely, x- and y-axes in figures B, D, F, H and J plot the residuals obtained from regressing the quadratic term in canon and math test scores, respectively, on the linear term in canon as well as the aforementioned set of covariates. The shaded areas represent the 95 percent confidence interval bands. Panels C to J present the averages using districts and bins as units for aggregation to facilitate visualization.

Figure A6. Mining *Canon* transfer stratified randomizations

a. Kernel density estimate for the coefficient of *Canon*



b. Kernel density estimate for the coefficient of *Canon* squared



Bandwidth: 0.2

Note: In the corresponding regressions, *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. The regressions do not include school characteristics or student characteristics.

Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A1. Effects of Canon on standardized academic achievement

	Dependent variable: Standardized test scores				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
			Panel A. Math scores		
Canon	0.0728	0.2286**	0.2302**	0.2513***	0.2255**
	(0.0468)	(0.0953)	(0.0962)	(0.0946)	(0.0946)
Canon squared		-0.0207**	-0.0208**	-0.0227***	-0.0202**
		(0.0084)	(0.0084)	(0.0083)	(0.0079)
Mining production			-0.0002	-0.0001	0.0037
			(0.0005)	(0.0004)	(0.0062)
Canon (lag)					-0.0004
					(0.0005)
Canon squared (lag)					-0.0208
					(0.0646)
Mining production (lag)					-0.0003
					(0.0002)
R-squared	0.1506	0.1507	0.1507	0.1604	0.0063
Number of students	2072351	2072351	2072351	2012798	2072351
			Panel B. Reading scores		
Canon	-0.0039	-0.0202	-0.0206	-0.0247	-0.0250
	(0.0175)	(0.0431)	(0.0435)	(0.0449)	(0.0446)
Canon squared		0.0022	0.0022	0.0023	0.0002
		(0.0037)	(0.0037)	(0.0038)	(0.0003)
Mining production			0.0001	0.0002	0.0021
			(0.0003)	(0.0002)	(0.0035)
Canon (lag)					0.0020
					(0.0036)
Canon squared (lag)					-0.0245
					(0.0384)
Mining production (lag)					0.0001
					(0.0001)
R-squared	0.2598	0.2598	0.2598	0.2895	0.0266
Number of students	2068281	2068281	2068281	2008941	2068281
Student controls	N	N	N	Y	N
School controls	N	N	N	Y	N

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Scores are standardized to the 2007 baseline, with a mean of 500 and standard deviation of 100. Mining and *Canon* correspond to the value of mining production per-capita and *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. School characteristics include: school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include: gender and mother language (Spanish/other) of the children. Test scores are standardized using the baseline mean (500 point) and standard deviation (100 points) for the test.

Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A2. Robustness check: Effects of Canon on academic achievement, excluding influential observations

	Dependent variable: Test scores		
	Methodology used to remove influential observations		
	Cook's distance	Welsch distance	DFITS
	(1)	(2)	(3)
	Panel A. Math scores		
Canon	26.6002**	28.6490***	26.5566**
	(10.3234)	(9.8892)	(10.3225)
Canon squared	-2.2151**	-2.4622***	-2.2081**
	(0.9597)	(0.8918)	(0.9600)
R-squared	0.1854	0.1716	0.1854
Number of students	1917894	1976426	1918024
	Panel B. Reading scores		
Canon	-1.1989	-0.6602	-1.2071
	(4.6879)	(4.5742)	(4.6900)
Canon squared	0.2007	0.1126	0.1999
	(0.4230)	(0.4006)	(0.4232)
R-squared	0.3062	0.2971	0.3062
Number of students	1915347	1973099	1915476
Student controls	Y	Y	Y
School controls	Y	Y	Y

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Mining and *Canon* correspond to the value of mining production per-capita and *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. School characteristics include: school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include: gender and mother language (Spanish/other) of the children.

Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A3-A. Robustness check: Evaluating parametric specification

	Dependent Variable: Test scores				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
			Panel A. Math scores		
Canon	7.2844	22.8601**	23.0187**	19.8230	18.5483
	(4.6782)	(9.5349)	(9.6193)	(14.0566)	(18.8563)
Canon squared		-2.0713**	-2.0797**	-0.3063	1.1966
		(0.8379)	(0.8408)	(3.7583)	(10.1663)
Mining production			-0.0222	-0.0251	-0.0246
			(0.0453)	(0.0472)	(0.0474)
Cubic canon				-0.1532	-0.4939
				(0.2647)	(1.7863)
Quartic canon					0.0209
					(0.0965)
F-test for quadratic specification			3.0781		
			0.0463		
F-test for nested models comparison:				0.3350	
Quadratic vs. cubic model				0.5628	
F-test for nested models comparison:					0.2444
Quadratic vs. quartic model					0.7832
Number of students	2072351	2072351	2072351	2072351	2072351
			Panel B. Reading scores		
Canon	-0.3903	-2.0187	-2.0558	-3.4096	-3.9064
	(1.7511)	(4.3111)	(4.3462)	(5.8862)	(7.4339)
Canon squared		0.2164	0.2184	0.9688	1.5554
		(0.3718)	(0.3728)	(1.5729)	(4.2779)
Mining production			0.0052	0.0039	0.0041
			(0.0257)	(0.0268)	(0.0267)
Cubic canon				-0.0648	-0.1977
				(0.1152)	(0.7827)
Quartic canon					0.0082
					(0.0430)
F-test for quadratic specification			0.2427		
			0.7846		
F-test for nested models comparison:				0.3168	
Quadratic vs. cubic model				0.5736	

F-test for nested models comparison:					0.1902
Quadratic vs. quartic model					0.8268
Number of students	2068281	2068281	2068281	2068281	2068281

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Mining and *Canon* correspond to the value of mining production per-capita and *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. School characteristics include: school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include: gender and mother language (Spanish/other) of the children.
Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A3-B. Robustness check: Machado and Santos Silva's Fixed Effects Quantile Regression Estimator

	Dependent variable: Math test scores								
	Quantile								
	(0.1)	(0.2)	(0.3)	(0.4)	(0.5)	(0.6)	(0.7)	(0.8)	(0.9)
Canon	7.2197***	11.5423***	14.8067***	17.7495***	20.7221***	23.8964***	27.4816***	31.9706***	38.7737***
	(2.5911)	(2.0794)	(1.7791)	(1.6118)	(1.5759)	(1.6943)	(1.9851)	(2.4953)	(3.4199)
Canon squared	-0.6793**	-1.0612***	-1.3496***	-1.6097***	-1.8723***	-2.1528***	-2.4696***	-2.8662***	-3.4673***
	(0.2911)	(0.2336)	(0.1999)	(0.1811)	(0.1771)	(0.1904)	(0.2230)	(0.2804)	(0.3843)
Mining production	0.0006	-0.0103	-0.0185	-0.0260	-0.0335*	-0.0415*	-0.0505**	-0.0618*	-0.0789*
	(0.0328)	(0.0263)	(0.0225)	(0.0204)	(0.0199)	(0.0215)	(0.0251)	(0.0316)	(0.0433)
Number of students	2072351	2072351	2072351	2072351	2072351	2072351	2072351	2072351	2072351
Student controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
School controls	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. Results are estimated for each conditional quantile based on the methods proposed by Machado and Santos Silva (2019).
Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A4. Robustness check: Non-producing districts in producing provinces

A4.1: Non-producing districts in producing provinces

	Dependent Variable: Scores			
	(1)	**(2)**	**(3)**	**(3)**
		Panel A. Math Scores		
Canon	15.3272**	42.9592***	42.9592***	43.7871***
	(7.2238)	(9.2733)	(9.2733)	(9.2556)
Canon squared		-4.0120***	-4.0120***	-4.1370***
		(0.8164)	(0.8164)	(0.8104)
R-squared	0.1280	0.1284	0.1284	0.1410
Number of students	407870	407870	407870	400926
		Panel B. Reading Scores		
Canon	-3.8087	-5.3912	-5.3912	-4.7101
	(2.4284)	(5.6054)	(5.6054)	(5.6430)
Canon squared		0.2281	0.2281	0.0985
		(0.4885)	(0.4885)	(0.4813)
R-squared	0.2669	0.2669	0.2669	0.2965
Number of students	407261	407261	407261	400343
Student controls	N	N	Y	Y
School controls	N	N	N	Y

A4.2: Non-producing districts in producing provinces excluding neighbors

	Dependent Variable: Scores			
	(1)	**(2)**	**(3)**	**(3)**
		Panel A. Math Scores		
Canon	10.4277	37.6692***	37.6692***	38.0808***
	(6.5299)	(10.1787)	(10.1787)	(10.1382)
Canon squared		-3.7287***	-3.7287***	-3.8315***
		(0.8925)	(0.8925)	(0.8816)
R-squared	0.1241	0.1246	0.1246	0.1388

Number of students	278997	278997	278997	273924
		Panel B. Reading Scores		
Canon	-5.8442**	-9.9492	-9.9492	-9.6133
	(2.8427)	(6.6099)	(6.6099)	(6.5722)
Canon squared		0.5581	0.5581	0.4507
		(0.5794)	(0.5794)	(0.5638)
R-squared	0.2565	0.2565	0.2565	0.2870
Number of students	278414	278414	278414	273374
Student controls	N	N	Y	Y
School controls	N	N	N	Y

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Canon corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. School characteristics include: school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include: gender and mother language (Spanish/other) of the children.
Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A5. Heterogeneous effects of *Canon*, adding the first lag of *Canon*

	All	Urban	Rural	Private	Public	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. Math scores			
Canon	22.5513**	26.3893**	18.9846*	-6.4909	24.6579***	25.8288**	19.5133**
	(9.4570)	(11.2499)	(10.2246)	(15.9171)	(8.8828)	(10.1614)	(9.2742)
Canon squared	-2.0215**	-2.3457**	-1.9617**	-0.1015	-2.1490***	-2.3228***	-1.7357**
	(0.7853)	(0.9287)	(0.8608)	(1.1735)	(0.7889)	(0.8479)	(0.7734)
Canon (lag)	-2.0750	-5.6025	3.9062	11.2144	-1.7002	-0.7738	-3.4785
	(6.4640)	(9.0584)	(7.3861)	(13.5169)	(6.1934)	(6.7937)	(6.5338)
Canon squared (lag)	0.3651	0.7299	-0.4908	-0.6438	0.3811	0.3165	0.4270
	(0.6222)	(0.8547)	(0.6862)	(1.0193)	(0.6502)	(0.6519)	(0.6418)
R-squared	0.0063	0.0092	0.0115	0.0103	0.0061	0.0056	0.0070
Number of students	2072351	1392163	660949	300937	1724326	1017586	1054761
				Panel B. Reading scores			
Canon	-2.7579	2.2402	0.0332	-24.4379**	0.0299	-2.0885	-3.4146
	(4.3115)	(4.5768)	(7.5611)	(10.4834)	(4.4246)	(4.1667)	(4.8807)
Canon squared	0.2444	-0.2401	0.0428	1.9187**	-0.0446	-0.0057	0.4771
	(0.3528)	(0.3919)	(0.6366)	(0.7803)	(0.3733)	(0.3388)	(0.4053)
Canon (lag)	-0.5900	-2.2541	3.5791	0.2607	0.3307	0.8649	-2.0367
	(4.0008)	(4.7002)	(5.5523)	(8.0025)	(3.8891)	(4.1912)	(4.2515)
Canon squared (lag)	0.1118	0.2666	-0.5023	0.3502	-0.0354	0.0772	0.1804
	(0.3789)	(0.4510)	(0.5618)	(0.5970)	(0.3996)	(0.4006)	(0.3972)
R-squared	0.0266	0.0273	0.0254	0.0228	0.0277	0.0287	0.0249

Number of students	2068281	1389735	659342	300799	1720622	1015828	1052449

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A6-A. Heterogenous effects of Canon on academic achievement, excluding influential observations using Cook's distance

	All	Urban	Rural	Private	Public	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. Math scores			
Canon	26.6002**	26.8111**	24.6180***	4.5098	27.6729***	28.3833**	24.8160**
	(10.3234)	(12.6886)	(8.4877)	(17.5618)	(9.8984)	(11.4835)	(9.7003)
Canon squared	-2.2151**	-2.1663*	-2.3715***	-0.8206	-2.2143**	-2.4134**	-2.0235**
	(0.9597)	(1.1360)	(0.8463)	(1.3310)	(0.9844)	(1.0529)	(0.9221)
R-squared	0.1854	0.1585	0.1511	0.0962	0.1781	0.1827	0.1893
Number of students	1917894	1305769	606850	296676	1621218	941919	975975
				Panel B. Reading scores			
Canon	-1.1989	2.4103	2.2851	-20.2116*	2.9793	-1.0618	-1.5192
	(4.6879)	(5.0684)	(7.6062)	(10.4568)	(4.7276)	(4.8219)	(5.0665)
Canon squared	0.2007	-0.1167	-0.2192	1.8116**	-0.2743	-0.0048	0.4205
	(0.4230)	(0.4408)	(0.7348)	(0.7889)	(0.4744)	(0.4469)	(0.4521)
R-squared	0.3062	0.2351	0.1818	0.1469	0.2653	0.3222	0.2913
Number of students	1915347	1304097	605984	296558	1618789	940808	974539

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A6-B. Heterogenous effects of Canon on academic achievement, excluding influential observations using Welsch's distance

	All	Urban	Rural	Private	Public	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. Math scores			
Canon	28.6490***	28.3599**	26.9155***	0.9736	30.2608***	31.4467***	25.9193***
	(9.8892)	(11.8830)	(9.3027)	(17.0329)	(9.5996)	(10.9419)	(9.3669)
Canon squared	-2.4622***	-2.4608**	-2.4629***	-0.5941	-2.5236***	-2.7551***	-2.1795**
	(0.8918)	(1.0460)	(0.8906)	(1.2843)	(0.9287)	(0.9780)	(0.8551)
R-squared	0.1716	0.1521	0.1363	0.0976	0.1635	0.1691	0.1755
Number of students	1976426	1335002	636003	298762	1677664	970088	1006338
				Panel B. Reading scores			
Canon	-0.6602	1.9248	3.8797	-22.2488**	3.5640	0.1425	-1.4990
	(4.5742)	(4.8681)	(7.5600)	(10.2461)	(4.6153)	(4.6964)	(4.9333)
Canon squared	0.1126	-0.1372	-0.3214	1.8254**	-0.3303	-0.1993	0.4264
	(0.4006)	(0.4139)	(0.7150)	(0.7672)	(0.4362)	(0.4160)	(0.4301)
R-squared	0.2971	0.2326	0.1736	0.1491	0.2559	0.3131	0.2824
Number of students	1973099	1332970	634718	298630	1674469	968635	1004464

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A6-C. Heterogenous effects of Canon on academic achievement, excluding influential observations using DFITs procedure

	All	Urban	Rural	Private	Public	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. Math scores			
Canon	26.5566**	26.7104**	24.6830***	4.4023	27.6337***	28.3237**	24.7884**
	(10.3225)	(12.6854)	(8.4879)	(17.5535)	(9.8978)	(11.4825)	(9.6982)
Canon squared	-2.2081**	-2.1574*	-2.3724***	-0.8124	-2.2065**	-2.4030**	-2.0207**
	(0.9600)	(1.1358)	(0.8472)	(1.3303)	(0.9843)	(1.0532)	(0.9220)
R-squared	0.1854	0.1585	0.1511	0.0962	0.1780	0.1827	0.1893
Number of students	1918024	1305837	606911	296682	1621342	941983	976041
				Panel B. Reading scores			
Canon	-1.2071	2.3845	2.3169	-20.1993*	2.9711	-1.0828	-1.5129
	(4.6900)	(5.0698)	(7.6105)	(10.4562)	(4.7307)	(4.8235)	(5.0662)
Canon squared	0.1999	-0.1144	-0.2249	1.8107**	-0.2755	-0.0062	0.4200
	(0.4232)	(0.4409)	(0.7350)	(0.7888)	(0.4745)	(0.4475)	(0.4521)
R-squared	0.3062	0.2351	0.1818	0.1469	0.2653	0.3222	0.2913
Number of students	1915476	1304164	606045	296563	1618913	940871	974605

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A7. Mechanisms based on school characteristics, all schools and private

	Dependent Variables					
	Enrollment	Percentage of teachers with long-term contract (at the school level)	Percentage of teachers with a tertiary education degree in a school teaching program	School has access to electricity	School has access to water	School has access to sanitation
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. All schools			
Canon	0.0116	0.0231	-0.0064	0.0697**	-0.0309	-0.0033
	(0.0084)	(0.0352)	(0.0075)	(0.0327)	(0.0221)	(0.0445)
Canon squared	-0.0011	-0.0038	0.0015*	-0.0046	0.0035*	0.0010
	(0.0008)	(0.0027)	(0.0008)	(0.0028)	(0.0018)	(0.0038)
R-squared	0.1560	0.2198	0.1081	0.2991	0.2901	0.2768
Number of schools	237541	128158	128158	588954	588952	588884
			Panel B. Private			
Canon	-0.0087	-0.0057	-0.0248	0.1962**	-0.0475	-0.0760
	(0.0138)	(0.0668)	(0.0371)	(0.0836)	(0.1261)	(0.1714)
Canon squared	0.0008	-0.0024	0.0056**	-0.0149**	0.0044	0.0045
	(0.0010)	(0.0049)	(0.0027)	(0.0063)	(0.0095)	(0.0128)
R-squared	0.2283	0.1154	0.1310	0.5618	0.4381	0.4286
Number of schools	28369	25507	25507	14026	14028	14024

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD, constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. None of the regressions include school characteristics. Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A8. Mechanisms based on school characteristics by area

	Dependent Variables					
	Enrollment	Percentage of teachers with long-term contract (at the school level)	Percentage of teachers with a tertiary education degree in a school teaching program	School has access to electricity	School has access to water	School has access to sanitation
	(1)	(2)	(4)	(5)	(6)	(7)
			Panel A. Urban			
Canon	0.0043	0.0392	-0.0018	0.0481**	-0.0490	0.0256
	(0.0241)	(0.0254)	(0.0105)	(0.0232)	(0.0335)	(0.0496)
Canon squared	-0.0007	-0.0033*	0.0014	-0.0028	0.0047*	-0.0013
	(0.0019)	(0.0020)	(0.0011)	(0.0018)	(0.0026)	(0.0038)
R-squared	0.2086	0.2404	0.1197	0.2293	0.3346	0.2442
Number of schools	59906	57004	57004	44686	44686	44674
			Panel B. Rural			
Canon	-0.0150	0.0037	-0.0080	0.1529*	0.1267*	0.1801**
	(0.0119)	(0.0510)	(0.0122)	(0.0796)	(0.0667)	(0.0826)
Canon squared	0.0011	-0.0016	0.0014	-0.0101	-0.0089*	-0.0146**
	(0.0009)	(0.0040)	(0.0010)	(0.0064)	(0.0051)	(0.0073)
R-squared	0.1876	0.3289	0.1416	0.3751	0.3286	0.4203
Number of schools	47932	41308	41308	43841	43839	43837

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. None of the regressions include school characteristics. Source: Authors' calculations based on data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A9. Mechanisms based on health factors by area

	Dependent variable				
	Individual experienced health complications in the past 4 weeks		Individual was sick in the past 4 weeks		Number of days individual couldn't work due to sickness in the past 4 weeks
	(All individuals)	(6 to 10 years of age)	(All individuals)	(6 to 10 years of age)	(14 - 65 years of age)
	(1)	(2)	(1)	(2)	(1)
			Panel A. Urban		
Canon	-0.1189***	-0.0931	-0.0645	-0.0314	0.0369
	(0.0422)	(0.0736)	(0.0427)	(0.0766)	(0.0713)
Canon squared	0.0111***	0.0141***	0.0045	0.0066	-0.0035
	(0.0032)	(0.0053)	(0.0032)	(0.0055)	(0.0054)
R-squared	0.0427	0.0345	0.0333	0.0433	0.0088
Number of observations	244821	23168	244821	23168	200560
			Panel B. Rural		
Canon	-0.0825**	-0.0348	-0.0582	-0.0854	0.0003
	(0.0355)	(0.0698)	(0.0382)	(0.0589)	(0.0727)
Canon squared	0.0088***	0.0068	0.0052*	0.0072	-0.0031
	(0.0029)	(0.0068)	(0.0030)	(0.0072)	(0.0056)
R-squared	0.1115	0.0829	0.0413	0.0780	0.0217
Number of observations	205969	26458	205969	26458	170078

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. None of the regressions include socio-demographic characteristics. Source: Authors' calculations based on ENAHO household survey data and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

Table A10. Robustness: Mechanisms: Local government expenditure and school-level characteristics, excluding influential observations

	Dependent Variables							
			Public schools only					
	Log of Local govern-ment expenditu-re in education and culture	School enroll-ment	School enroll-ment	Percentage of teachers with long-term contract (at the school level)	Percentage of teachers with a tertiary education degree in a school teaching program	School has access to electricity	School has access to water	School has access to sanitation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. influential observations removed using Cook's distance							
Canon	0.0642***	0.0091	-0.0185	-0.0358	0.0017	0.1395***	0.0461	0.1365***
	(0.0119)	(0.0085)	(0.0447)	(0.0349)	(0.0064)	(0.0403)	(0.0356)	(0.0502)
Canon squared	-0.0077***	-0.0011	0.0012	0.0016	0.0002	-0.0086**	-0.0019	-0.0086**
	(0.0010)	(0.0008)	(0.0036)	(0.0027)	(0.0005)	(0.0035)	(0.0028)	(0.0041)
R-squared	0.6292	0.1943	0.3993	0.3294	0.1275	0.3456	0.3294	0.3810
Number of districts	9556							
Number of schools		197090	40752	66441	66441	74659	74657	74650
	B. influential observations removed using Welsch distance							
Canon	0.0812***	0.0092	-0.0179	-0.0358	0.0017	0.1396***	0.0460	0.1365***
	(0.0131)	(0.0085)	(0.0447)	(0.0349)	(0.0064)	(0.0403)	(0.0356)	(0.0502)
Canon squared	-0.0089***	-0.0011	0.0011	0.0016	0.0002	-0.0087**	-0.0019	-0.0086**
	(0.0011)	(0.0008)	(0.0036)	(0.0027)	(0.0005)	(0.0035)	(0.0028)	(0.0041)

R-squared	0.6185	0.1942	0.3990	0.3294	0.1275	0.3456	0.3294	0.3810
Number of districts	9704							
Number of schools		197102	40753	66443	66443	74663	74661	74654
	C. influential observations removed using the DFITS procedure							
Canon	0.0641***	0.0085	-0.0131	-0.0375	0.0029	0.1406***	0.0536	0.1461***
	(0.0119)	(0.0085)	(0.0439)	(0.0338)	(0.0063)	(0.0382)	(0.0341)	(0.0496)
	0.00							
Canon squared	-0.0077***	-0.0011	0.0006	0.0018	0.0001	-0.0089***	-0.0032	-0.0096**
	(0.0010)	(0.0008)	(0.0036)	(0.0026)	(0.0005)	(0.0032)	(0.0027)	(0.0043)
R-squared	0.6286	0.1799	0.3714	0.3282	0.1275	0.3430	0.3261	0.3804
Number of districts	9551							
Number of schools		203672	42342	69002	69002	77859	77857	77850

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A11. Robustness: Mechanisms: Role of health factors, excluding influential observations

	Dependent variable				
	Individual experienced health complications in the past 4 weeks		Individual was sick in the past 4 weeks		Number of days individual couldn't work due to sickness in the past 4 weeks
	(All individuals)	(6 to 10 years of age)	(All individuals)	(6 to 10 years of age)	(14 - 65 years of age)
	A. influential observations removed using Cook's distance				
Canon	-0.0859***	-0.0314	-0.0613**	-0.0828	-0.0047
	(0.0293)	(0.0583)	(0.0299)	(0.0513)	(0.0571)
Canon squared	0.0089***	0.0062	0.0051**	0.0053	-0.0019
	(0.0024)	(0.0054)	(0.0024)	(0.0042)	(0.0045)
Observable characteristics	No	No	No	No	No
R-squared	0.0685	0.0579	0.0349	0.0605	0.0141
Number of observations	382694	41768	382694	41768	315032
	B. influential observations removed using Welsch distance				
Canon	-0.0872***	-0.0433	-0.0621**	-0.0906*	-0.0016
	(0.0287)	(0.0566)	(0.0296)	(0.0503)	(0.0525)
Canon squared	0.0089***	0.0088*	0.0049**	0.0084**	-0.0020
	(0.0024)	(0.0045)	(0.0023)	(0.0040)	(0.0042)
Observable characteristics	No	No	No	No	No
R-squared	0.0695	0.0577	0.0347	0.0597	0.0143
Number of observations	403986	44242	403986	44242	332343
	C. influential observations removed using the DFITS procedure				

Canon	-0.0860***	-0.0305	-0.0610**	-0.0828	-0.0041
	(0.0293)	(0.0582)	(0.0299)	(0.0513)	(0.0571)
Canon squared	0.0090***	0.0061	0.0051**	0.0053	-0.0020
	(0.0024)	(0.0054)	(0.0024)	(0.0042)	(0.0044)
Observable characteristics	No	No	No	No	No
R-squared	0.0685	0.0579	0.0349	0.0606	0.0141
Number of observations	382761	41776	382761	41776	315084

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010.
Source: Authors' calculations based on ENAHO household survey and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

Table A12. Robustness: Mechanisms: Local government expenditure and school-level characteristics, including the first lag of Canon

	Dependent Variables							
			Public schools only					
	Log of Local government expenditure in education and culture	School enroll-ment	School enroll-ment	Percentage of teachers with long-term contract (at the school level)	Percentage of teachers with a tertiary education degree in a school teaching program	School has access to electricity	School has access to water	School has access to sanitation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Canon	0.0673**	0.0130	-0.0229	-0.0163	-0.0211	0.1882**	-0.1024	-0.1721
	(0.0299)	(0.0085)	(0.0320)	(0.0604)	(0.0397)	(0.0916)	(0.1549)	(0.2135)
Canon squared	-0.0092**	-0.0012	0.0010	-0.0015	0.0059**	-0.0150**	0.0071	0.0096
	(0.0038)	(0.0008)	(0.0023)	(0.0045)	(0.0028)	(0.0068)	(0.0113)	(0.0154)
Canon (lag)	0.1481***	0.0075	-0.0024	0.0743	0.0043	-0.0082	-0.2615*	-0.3069
	(0.0283)	(0.0087)	(0.0176)	(0.0532)	(0.0335)	(0.0816)	(0.1474)	(0.2113)
Canon squared (lag)	-0.0109***	-0.0003	-0.0003	-0.0094**	-0.0024	0.0000	0.0187*	0.0232
	(0.0037)	(0.0006)	(0.0012)	(0.0041)	(0.0025)	(0.0062)	(0.0110)	(0.0158)
R-squared	0.4656	0.1557	0.5337	0.1196	0.1307	0.5619	0.4390	0.4301
Number of districts	9947							

Number of schools	237357	14134	25535	25535	14033	14035	14031

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.

Table A13. Robustness: Mechanisms: Role of health factors, including the first lag of Canon

	Dependent variable				
	Individual experienced health complications in the past 4 weeks		Individual was sick in the past 4 weeks		Number of days individual couldn't work due to sickness in the past 4 weeks
	(All individuals)	(6 to 10 years of age)	(All individuals)	(6 to 10 years of age)	(14 - 65 years of age)
Canon	-0.1047***	-0.0704	-0.0745***	-0.0804*	-0.0659
	(0.0304)	(0.0545)	(0.0278)	(0.0476)	(0.0488)
Canon squared	0.0101***	0.0105**	0.0059***	0.0078*	0.0028
	(0.0025)	(0.0046)	(0.0022)	(0.0041)	(0.0037)
Canon (lag)	-0.0429	-0.0190	-0.0630***	0.0230	-0.2201***
	(0.0269)	(0.0433)	(0.0222)	(0.0452)	(0.0567)
Canon squared (lag)	0.0031	0.0020	0.0044**	-0.0037	0.0162***
	(0.0022)	(0.0039)	(0.0018)	(0.0038)	(0.0046)
Observable characteristics	No	No	No	No	No
R-squared	0.0693	0.0559	0.0348	0.0569	0.0138
Number of observations	450615	49607	450615	49607	370499

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010.
Source: Authors' calculations based on ENAHO household survey and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

Table A14. Robustness check: Using province by year fixed-effects

	Dependent variable: Test scores			
	(1)	**(2)**	**(3)**	**(4)**
	Panel A. Math scores			
Canon	5.7630	19.1436**	19.6064**	18.9721**
	(4.5815)	(8.4336)	(8.5849)	(8.7281)
Canon squared		-2.1161**	-2.1215**	-1.9871**
		(0.8344)	(0.8353)	(0.8586)
R-squared	0.1624	0.1624	0.1624	0.1721
Number of students	2072351	2072351	2072351	2012798
	Panel B. Reading scores			
Canon	4.6803	5.4102	5.8980	3.6609
	(2.8960)	(5.9818)	(6.0469)	(6.2816)
Canon squared		-0.1149	-0.1212	0.1738
		(0.5675)	(0.5685)	(0.6063)
R-squared	0.2663	0.2663	0.2663	0.2959
Number of students	2068281	2068281	2068281	2008941
Mining production	N	N	Y	Y
Student controls	N	N	N	Y
School controls	N	N	N	Y

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by province-year. None of the regressions include socio-demographic characteristics. Source: Authors' calculations based on ENAHO household survey data and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

Table A15. Robustness check: Dropping 2007 from the Sample

	Dependent variable: Test scores			
	(1)	(2)	(3)	(4)
	Panel A. Math scores			
Canon	8.8023*	23.3800**	23.6583**	25.3486**
	(4.8593)	(10.4736)	(10.5404)	(10.3596)
Canon squared		-1.9838**	-2.0037**	-2.2139**
		(0.9441)	(0.9467)	(0.9355)
R-squared	0.1577	0.1577	0.1577	0.1680
Number of students	1714995	1714995	1714995	1668620
	Panel B. Reading scores			
Canon	1.9766	2.5837	2.6863	3.1588
	(2.0879)	(5.8112)	(5.8469)	(5.6241)
Canon squared		-0.0824	-0.0899	-0.2042
		(0.5154)	(0.5170)	(0.4996)
R-squared	0.2555	0.2555	0.2555	0.2862
Number of students	1715557	1715557	1715557	1669111
Student controls	N	N	N	Y
School controls	N	N	N	Y

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by province-year. None of the regressions include socio-demographic characteristics. Source: Authors' calculations based on ENAHO household survey data and data from Peru's Ministry of Finance and Peru's Ministry of Mines and Energy.

Table A16. Heterogeneous effects of *Canon* on standardized test scores

	All (1)	Urban (2)	Rural (3)	Private (4)	Public (5)	Female (6)	Male (7)
				Panel A. Math scores			
Canon	0.2513***	0.2626**	0.2174**	-0.0490	0.2701***	0.2856***	0.2189**
	(0.0946)	(0.1130)	(0.0986)	(0.1662)	(0.0924)	(0.1042)	(0.0906)
Canon squared	-0.0227***	-0.0236**	-0.0218**	-0.0010	-0.0241***	-0.0256***	-0.0199**
	(0.0083)	(0.0098)	(0.0086)	(0.0125)	(0.0086)	(0.0092)	(0.0079)
R-squared	0.1604	0.1472	0.1278	0.0986	0.1519	0.1582	0.1646
Number of students	2012798	1353896	653410	299441	1713357	987444	1025354
				Panel B. Reading scores			
Canon	-0.0247	0.0068	0.0097	-0.2477**	0.0176	-0.0206	-0.0287
	(0.0449)	(0.0467)	(0.0744)	(0.0981)	(0.0457)	(0.0459)	(0.0482)
Canon squared	0.0023	-0.0008	-0.0004	0.0204***	-0.0022	0.0005	0.0041
	(0.0038)	(0.0040)	(0.0065)	(0.0073)	(0.0041)	(0.0039)	(0.0041)
R-squared	0.2895	0.2303	0.1693	0.1505	0.2483	0.3054	0.2751
Number of students	2008941	1351621	651838	299302	1709639	985751	1023190

Note: Robust standard errors clustered at the district level in parentheses. * Significant at ten percent; ** significant at five percent; *** significant at one percent. Scores are standardized to the 2007 baseline, with a mean of 500 and standard deviation of 100. *Canon* corresponds to the value of *Canon* per-capita, in thousands of USD at constant prices of 2010. All regressions include the value of mining production (constant USD, 2010=100), dummies for type of province (i.e., producer and non-producer in producing district), and fixed effects at the district level and by year. We also control for school and student characteristics. School characteristics include school day (full-day, half-day morning or half-day afternoon); school administration type (public/private), and school type (one-teacher school/full grade). Student characteristics include gender and mother language (Spanish/other) of the children. Source: Authors' calculations based data from Peru's Ministries of Education, of Finance, of Energy and Mines, and INEI.