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The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru

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Abstract

This paper studies the impact of mining activity on socioeconomic outcomes in local communities in Peru. In the last two decades, the value of Peruvian mining exports has grown by fifteen times; and since a decade ago, one-half of fiscal revenues from mining have been devolved to local governments in producing regions. Has this boom benefitted people in local communities? We find evidence that producing districts have larger consumption per capita and lower poverty rates than otherwise similar districts. However, these positive impacts decrease drastically with administrative and geographic distance from mining centers. Moreover, consumption inequality within producing districts is higher than in comparable nonproducing districts. This dual effect of mining is partially accounted for by the better educated immigrants required and attracted by mining activity. The inequalizing impact of mining, both across and within districts, may explain the social discontent with mining in Peru, despite its enormous revenues.

JEL: D7, H7, O1, Q3

Keywords: Natural resources, Mining, Poverty, Inequality, Commodity Boom, Peru

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1. Introduction

To which extent do local communities benefit from extractive natural resources and commodity booms? The question has been subject to wide but inconclusive investigations. This paper utilizes new data on mining activity and government transfers in Peru to investigate the effect of mining and resource windfalls on socioeconomic outcomes at the district level, the lowest administrative unit in the country.[1]

Peru is in its second decade of an impressive mining boom. After decades of relative stagnation, the value of mining exports doubled in the 1990s and then rose by more than seven times in the following decade. By the early 2010s, the value of Peru´s mining exports averaged nearly 25 billion US dollars, or 14% of GDP and over 50% of total exports. At the beginning of the current decade, Peru was among the five largest producers of silver, zinc, tin, lead, copper, gold, and mercury in the world.

Local Governments in producing regions are benefitting generously from mining activities. The central Government transfers 50% of the taxes levied on mining companies to local authorities in mining regions. This sharing scheme, called the *Mining Canon*, was implemented to decentralize resource windfalls and allocates funds to district, province, and regional governments according to a distribution rule that favors producing localities. This sharing agreement was developed in the context of a broader decentralization process that began in 2002.[2] The Mining Canon's distribution rule is dictated and revised by national law.[3] In 2007, the year of our analysis, the overall budget envelope of the Canon amounted to approximately 1.6 billion US dollars.

Yet, despite these generous transfers, the dramatic expansion of mining production has been accompanied by rising social tensions. In 2009, the Office of the Ombudsman (*Defensoría del Pueblo*) reported 268 social conflicts in Peru, of which 38 percent were related to mining activities. Major confrontations involved violence and the use of firearms, leading to death and injuries among protesters

[1] In Peru, sub-national administrative units are called regions, provinces, and districts, in decreasing order of size.

[2] To avoid the fiscal crises that had plagued earlier episodes of decentralization in Latin America, decentralization in Peru was heavily anchored around fiscal neutrality (World Bank, 2003). The ability of sub-national Governments to borrow was strictly limited by law, and the central Government imposed strong fiduciary requirements for spending (such as the need to submit proposals and receive clearance from the central Government for large capital investments). For districts, a law on participatory budgeting was also passed requiring local authorities, who are elected every four years, to consult each year with their constituency and civil society in planning the budget.

[3] The Canon's rule is as follows: 50 percent of mining tax revenues are distributed back to subnational governments; of this amount, 10 percent goes directly to the corresponding producing district; 25 percent is distributed among all districts in a producing province; 40 percent is distributed among all districts in a producing region; and the remaining 25 percent is transferred to regional Governments and universities. Apart from the 10 percent transferred directly to producing districts, the allocation of the Canon across all (producing and non-producing districts) depends on district characteristics that include population size and socioeconomic conditions.

and the police (Taylor, 2011). These social tensions are a major concern for policy makers, not least because they have even halted or prevented large mining ventures: It is estimated that by 2014 mining investment lost due to social conflicts amounted to $8-12 billion (4-6% of GDP).[4] While many protesters cite environmental concerns, case studies suggest that the underlying reasons are often more complex, involving revenue sharing disputes between mining companies, local authorities, and local populations (Arellano-Yanguas, 2011). Poor management of the Canon also appears to add to the discontent (Hinojosa, 2011).

In this paper we use variation in mining across Peruvian districts to investigate the impact of mining activity and government transfers on local socioeconomic outcomes. The analysis uses a unique, district-level dataset that merges administrative data on local mining production and transfers from central to local governments with census and survey-based data on average consumption, poverty, and inequality. The main year of observation is 2007, when the latest national census took place.

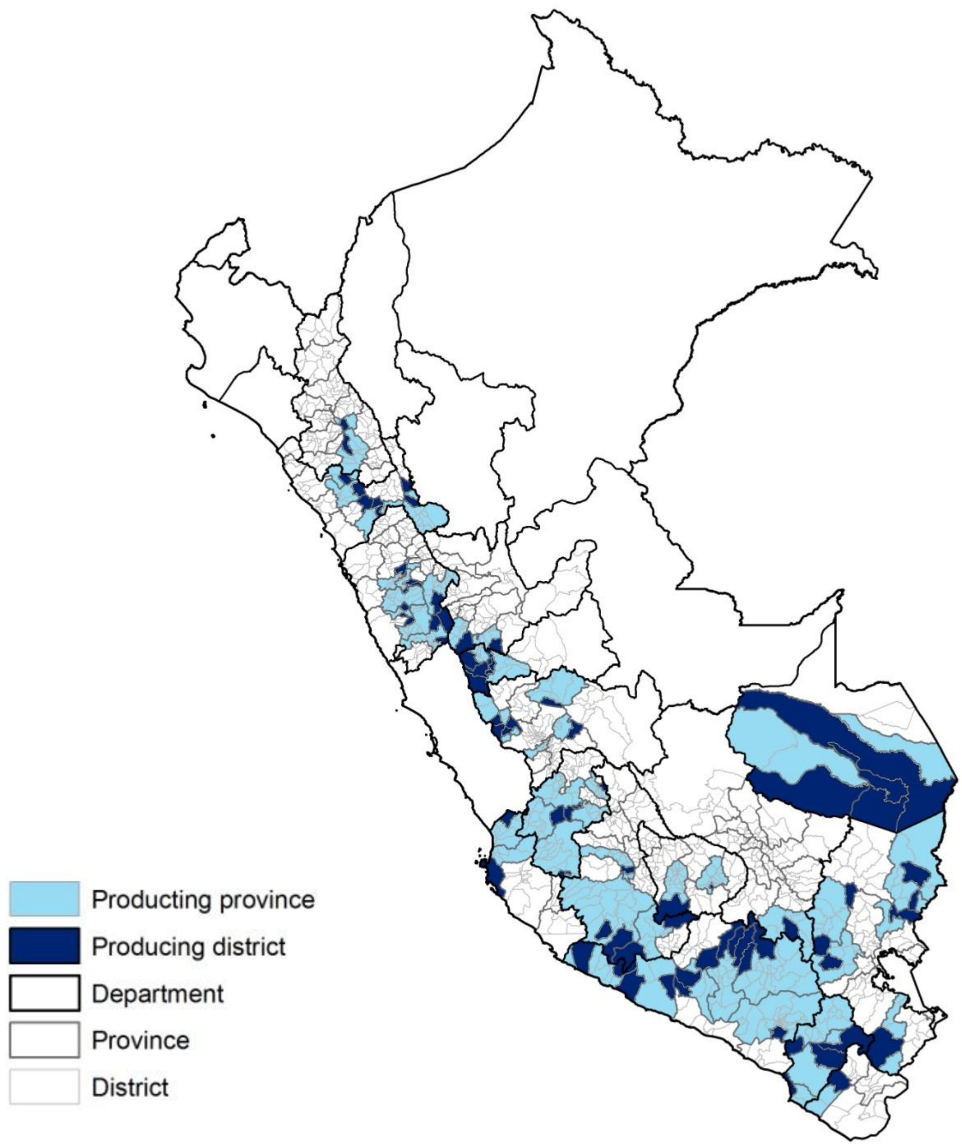
Our identification strategy is based on comparing socioeconomic outcomes in mining producing districts with outcomes in neighboring nonproducing districts of otherwise similar characteristics. Our premise is that, while economic and political factors may influence international patterns of mining activity, at lower administrative and geographic levels the location of mining production is primarily dictated by geological factors. By comparing neighboring or nearby districts and controlling for initial conditions, we can reduce biases related to endogenous location decisions. Figure 1 reports the location of mining districts and provinces across the Peruvian territory. It shows that mining is concentrated in the Andean region and in the Amazon basin. To reduce potential omitted variable biases, we restrict the analysis to regions that report mining activity, and we exclude the region of Lima (where the influential and populous capital city is located). Our sample consists of 89 mining producing districts and 1127 nonproducing districts spread over 141 provinces and 16 regions in Peru.

Since we are able to identify the location where the mineral is extracted down to the lowest administrative level, we can estimate mining effects on socio-economic outcomes with greater local accuracy and specificity. We can also study the extent to which local mining effects vary with the geographic and administrative distance between producing and nonproducing districts. This represents an improvement with respect to related studies, which have focused on the aggregate impact of oil-related windfalls over large regions. In contrast with mineral mines, oil fields and oil wells tend to be spread over several local administrations, making it necessary to conduct impact analyses at higher

[4] The figures on investment lost due to conflicts are based on Abusada (2014) and own calculations using information from the Ministry of Energy and Mining (MINEM).

levels of aggregation (Michaels, 2010). This runs the risk of missing some of the specific local effects and suffering from aggregation bias (Caselli and Michaels, 2013).

Figure 1: Mineral production in Peru (excluding Lima), 2007



Several findings emerge. Mining activity appears to be beneficial for districts where production takes place, resulting in higher consumption per capita and lower poverty and extreme poverty rates than in comparable nonproducing districts. The benefits of mining activity, however, seem to be unevenly distributed: Consumption inequality, as captured by the Gini coefficient, is higher in all districts of mining provinces and particularly in producing districts. Moreover, the benefits of mining activity are localized to producing districts, with no discernable spillovers to other districts in the same province, not even to close geographic neighbors. Therefore, mining appears to lead also to higher inequality *across* districts.

After conducting a few robustness exercises, which confirm the basic results, we turn our attention to assessing the impact of the Mining Canon itself and to understanding the mechanisms behind the dual effect of mining activity. Regarding the Mining Canon, we use an instrumental variable procedure to deal with its endogeneity and evaluate its impact.[5] We construct an instrument based on a revenue distribution rule that accounts for the district's jurisdictional location and population but abstracts from other socioeconomic characteristics. Once instrumented, the Canon does not seem to have a detrimental effect on districts' per capita consumption, poverty, or inequality.[6] However, it does not appear to have a beneficial effect either. This lack of impact is in line with some of the findings from studies focusing on oil exploitation (Caselli and Michaels, 2013). It calls into question the usefulness of revenue sharing agreements without strong monitoring and capacity building for subnational governments (Bardhan and Mookherjee, 2006; Loayza, Rigolini and Calvo-Gonzalez, 2014).

In order to understand the mechanisms behind the positive (average) and negative (distributional) effects of mining activity, we consider the differences between migrant and native populations. Producing districts have a larger immigrant population than non-producing districts in the same province or in other, non-producing, provinces. Moreover, producing districts have better educational indicators than nonproducing districts, but alas, not because of differences across native populations but because of their better-educated immigrants who were drawn because of mining. On the positive side, native populations in producing districts do have a larger share of salaried workers than native populations in nonproducing districts. These results suggest that the better *average* outcomes enjoyed by producing districts are, in part, explained by the better-educated (and presumably better-paid) immigrants that mining activities require and attract and, only to some extent, explained by the jobs that some natives (presumably the more qualified) are able to get. This may not only explain the better *average* effects, but also the worse *distributional* outcomes regarding higher inequality.

Our findings add to a rich literature that investigates the impact of natural resource exploitation. Early cross-country studies based on cross-sectional analyses (Sachs and Warner, 1995 and 2001) tend to find a negative association between natural resource abundance and economic growth. However,

[5] The Mining Canon distribution rule assigns larger allocations to poorer and less developed districts.
[6] The OLS results show that a larger Mining Canon transfer is associated with *lower* consumption per capita and *higher* poverty index.

studies exploiting both cross-sectional and time-series variation find no effect or even a positive one (Manzano and Rigobon, 2006; Raddatz, 2007). Differences in institutional settings and time horizons (short vs. longer term) may explain in part these contrasting results (Mehlum, Moene and Torvik, 2006; Collier and Goderis, 2008; van der Ploeg, 2011). Notwithstanding their contribution, cross-country studies have suffered from uneven data quality and limited treatment of omitted variables that may correlate with resource abundance.

More recent studies have attempted to solve some of these pitfalls by exploiting variation of natural resource exploitation within national boundaries. These studies have mostly focused on oil extraction. A pattern is beginning to emerge. Michaels (2010) studies the impact of oil abundance in Southern U.S. counties on their long term development. It finds that oil abundance increases local employment, population growth, per capita income, and quality of infrastructure.[7] In developing countries with inferior institutional capacity, however, the picture seems to reverse. Caselli and Michaels (2013) looks at the impact of backward linkages and revenue windfalls from oil production across municipalities of similar characteristics in Brazil. It finds no impact on GDP; and despite higher reported municipal spending on a range of budgetary items, the paper finds little impact on social transfers, public good provision, infrastructure, and household income. Moreover, Dube and Vargas (2006) finds that higher oil prices in Colombia boost conflict over the ownership of resource production. Thanks to a greater ability to determine the location of mining activity and the use of different socioeconomic outcomes, our analysis can measure local effects with more precision and make progress in understand their mechanisms.

Our cross-district analysis can be regarded as complementary to case-specific studies. For instance, our findings can help put in perspective the results of Aragon and Rud (2013), which studies the effects of the Yanacocha gold mine in Peru, the second largest in the world. It finds a geographically widespread positive impact. The Yanacocha mine may, however, represent a best-case scenario for two reasons. First, its sheer size may extend its impact beyond its location. Second, as Aragon and Rud (2013) observes, local living standards improved only after international shareholders put pressure on Yanacocha's management to expand local procurement of inputs.

Finally, our analysis contributes, albeit tangentially, to an emerging literature on the political economy of fiscal transfers and their use (Brollo et al., 2013). Studying local financing in Brazilian municipalities, Litschig (2012) finds that local officials handle revenues derived from natural resources

[7] At a higher level of aggregation, however, Papyrakis and Gerlagh (2007) find a negative US state-level correlation between resource extraction and growth.

differently than they do other transfers from the central Government: Only the latter seems to contribute to human capital accumulation and poverty alleviation. These differences may stem from a greater ability of local officials to capture commodity-related revenues, which is particularly pronounced when citizens have little knowledge about their magnitude (Monteiro and Ferraz, 2010).

The paper is organized as follows. Section 2 presents the data and empirical methodology. Section 3 shows and discusses the results. Section 4 concludes.

2. Data and Methodology

2.1 Data

The unit of observation and analysis is the district, which is the smallest administrative unit in the country. In Peru, a group of districts forms a province and a group of provinces forms a region. The boundaries between them are based on historical and political jurisdictions and revised only rarely.[8] The advantage of using district-level analysis is that it allows the most precise identification of local effects resulting from mining activity. We only work with districts belonging to regions where some mining activity took place in the five years prior to the year of observation, 2007, and we exclude districts in the region of Lima, which contains the country's capital and is an outlier in most respects. The resulting sample consists of 1216 districts in 141 provinces and 16 regions. Appendix Table A1 provides information on definitions and sources of all variables used in the paper, and Appendix Table A2 presents some summary statistics across groups of districts.

As dependent variables, we consider a set of socioeconomic outcome indicators (at the district level). For our purposes, the most important of them are derived from the country's "poverty map" for 2007: average per capita consumption, poverty and extreme poverty headcount indexes, and the Gini coefficient of consumption inequality. The poverty map was developed by the Peruvian Statistical Institute, combining data from the 2007 Census and the 2007 National Household Survey (INEI, 2009) and following a methodology based on Hentschel, Lanjouw, Lanjouw, and Poggi (2000). In some applications, we also use indicators directly derived from the National Censuses of 2007 and 1993: illiteracy rate, average years of education of the adult population, immigration rate, employment rate, and public and private infrastructure measures.

We use two sets of explanatory variables: The first and most important are indicators of the location and magnitude of mining activity, as well as measures of fiscal revenues accruing to districts according to the Mining Canon Law; the second one is a set of control variables chosen to account for

[8] Peru is divided into 25 regions, 195 provinces, and 1841 districts.

initial differences across districts. Using plant-level mining data from the Peruvian Ministry of Energy and Mining (MINEM), we distinguish three types of districts within mining regions: *Producing districts*, which host a mining facility with some mineral production during 2002-2006 and receive the largest share of the Canon; *non-producing districts in producing provinces*, which, despite not having a mining facility, receive a portion of the Canon; and *non-producing districts in non-producing provinces*, which still receive a share of the Canon, albeit the smallest among the three types of districts. Our sample contains 89 producing districts, 462 non-producing districts in producing provinces, and 665 non-producing districts in non-producing provinces.

Apart from these categorical variables (that is, dummy variables corresponding to the three types of districts), we also use information on the magnitude of mining activity and related fiscal revenues. The magnitude of mining activity at the district level is measured as the accumulated value of mineral production by all mining facilities within the district for the period 2002-2006. We obtain the value of mineral production by combining data on production quantities by type of mineral with international prices per mineral, both reported by the Ministry of Energy and Mining (MINEM). Similarly, *Canon* revenue at the district level is the accumulated value of fiscal transfers received by each district during 2002-2006, as reported by the Ministry of Economy and Finance (MEF).

The second set of explanatory variables consists of control variables, which account for differences across districts that are unrelated to mining activity or its revenues. First, we include time-invariant district characteristics, such as surface area, altitude, and a binary variable indicating whether the district is a provincial capital. Second, we include district-specific initial conditions, taken from the 1993 Census, such as total population, percentage of rural population, percentage of households with access to clean water and sanitation, percentage of households with electricity, the illiteracy rate, and the percentage of the working-age population with paid work. The last control variable involves fiscal transfers other than those related to mining activity, grouped under the program "Foncomun"; our measure consists of the accumulated Foncomun transfers received by each district during 2002-2006, as reported by the Ministry of Economy and Finance.

2.2 Methodology

Our identification strategy relies upon comparing localities that are spatially close and institutionally similar but differ regarding mining activity. In order to work with similar localities, we use the administrative demarcation of localities into districts, provinces, and regions, focusing on the comparisons between districts belonging to the same region or province. We conduct these comparisons by means of several exercises, which are explained in detail in the following section. Using terms from experimental design, we can consider having two treatment groups --producing districts and nonproducing districts in producing provinces-- and a control group --districts in nonproducing provinces. The comparisons of interest are between each of the treatment groups with the control group, and between the treatment groups with each other.

The quality of the identification strategy depends on whether treatment and control districts were similar before the "treatment" started, that is, before the mining boom. As mentioned previously, mining activity picked up in Peru in the 2000s, with the international commodity boom and the propitious macroeconomic and business conditions in the country. However, mining has been historically important for Peru, and there has always been some mining in certain areas of the country. There are, therefore, reasons to believe that producing and nonproducing districts were not initially similar.

Ideally, we would have liked to have a baseline with information on the outcome variables of interest (income, poverty, and inequality) at an initial period. Then, we could have conducted a difference-in-difference type of comparison. Unfortunately, however, a poverty map before the mining boom is unavailable and cannot be constructed: The previous census, conducted in 1993, was not accompanied by a household survey that would provide income or consumption information.

Nevertheless, we are able to check for some initial differences across districts, prior to the mining boom, using information from the 1993 Census. We consider district-level initial conditions regarding population, education, work, and infrastructure. We conduct the comparison across treatment and control groups by applying the following regression:

$$X_d = \alpha_0 + \alpha_1 \mathbb{I}_d[PD] + \alpha_2 \mathbb{I}_d[NPDPP] + \alpha_3 D_d + \nu_R + \nu_p + \varepsilon_d \qquad (1)$$

where, d denotes district, X_d represents a given initial condition, $\mathbb{I}_d[PD]$ is a binary variable that takes the value of 1 if the district is producing and 0 otherwise, $\mathbb{I}_d[NPDPP]$ is a binary variable that takes value of 1 if the district is non-producing in a producing province and 0 otherwise, D_d is a set of time-invariant district characteristics, ν_R is a region fixed effect, ν_p is a province fixed effect, and ε_{pd} is an error term.

By including or not region and province fixed effects, the coefficients $\alpha_1$and α_2 convey different comparisons, which are presented in the columns of Table 1. Thus, when neither region nor province fixed effects are included, α_1 estimates the difference between the means of producing districts (treatment 1) and districts in nonproducing provinces (control) in any region; and α_2 estimates the difference in means between nonproducing districts in producing provinces (treatment 2) and districts in nonproducing provinces (control) in any region. These estimates are presented in the first two columns under the heading "Across and Within regions." When region fixed effects are included but not province fixed effects, the meaning of $\alpha_1$and α_2 is similar as above but the comparison is restricted to districts within the same region. These estimates are presented in the intermediate two columns under the heading "Within Region." Finally, when province fixed effects are included, $\mathbb{I}_d[NPDPP]$ drops out, and α_1 estimates the difference in means between producing districts (treatment 1) and nonproducing districts in the same province (treatment 2).[9] These estimates are presented in the last column under the heading "Within Province."

The results in Table 1 indicate that as of 1993 there were differences between producing and nonproducing districts and, in general, between treatment and control groups. Moreover, these differences were rather in favor of districts in producing provinces, especially those where mining took place. These differences are reduced when we compare districts within the same province, but do not fully disappear. These results highlight the importance of controlling for province effects and suggest the need to include controls for initial conditions, which we do in the main empirical analysis of the paper.

[9] Naturally, when province fixed effects are included, region fixed effects become redundant.

TABLE 1. INITIAL CONDITIONS IN 1993

OLS: SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Across and Within Regions		Within Region		Within Province
	Producing Districts vs Districts in Nonproducing Provinces (α_1)	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (α_2)*	*Producing Districts vs Districts in Nonproducing Provinces (α_1)*	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (α_2)*	*Producing Districts vs Nonproducing districts in the same Province (α_1)*
1993 Census					
A) Log of Population in 1993	-0.032	-0.435***	0.143	-0.217***	0.441***
	(0.119)	(0.059)	(0.113)	(0.058)	(0.107)
B) % of Rural Population in 1993	-13.644***	-7.574***	-9.687***	-5.909***	-4.219
	(3.054)	(1.497)	(2.735)	(1.468)	(2.628)
C) % of Population that is Illiterate in 1993	-6.615***	-3.196***	-4.289***	-2.764***	-1.306
	(1.426)	(0.735)	(1.381)	(0.729)	(1.225)
D) % of Population with Secondary Education or Above in 1993	8.079***	2.070***	5.726***	0.922	4.178***
	(1.420)	(0.674)	(1.222)	(0.584)	(1.136)
E) % of Population with Paid Work at the Time of Census in 1993	2.377***	1.036**	1.971**	0.698	1.683*
	(0.885)	(0.453)	(0.917)	(0.495)	(0.918)
F) % of Household with Water Supply in 1993	6.691***	4.012***	3.715*	2.552**	1.779
	(2.087)	(1.114)	(1.962)	(1.136)	(1.985)
G) % of Households with Electricity in 1993	15.214***	1.629	13.762***	3.311***	8.706***
	(3.114)	(1.408)	(2.859)	(1.245)	(2.991)
Controls:					
Provincial Capital Dummies, Log of Area, and Log of Altitude	YES	YES	YES	YES	YES
Region Dummies	-	-	YES	YES	-
Province Dummies	-	-	-	-	YES
Observations	1,216	1,216	1,216	1,216	1,216

3. Results

Using the sample and data outlined above, we conduct the following empirical exercises. First, we present the basic results of comparing the treatment and control groups. Second, we conduct some variations of the basic specification to check the robustness of the results. Third, we study to what extent the effects of mining activity are localized geographically, in the sense of applying only to producing districts without spillovers to their neighbors. Fourth, we consider whether the Mining Canon has an effect on its own and whether it affects the basic results of mining activity. And fifth, we examine a likely mechanism by contrasting outcomes from the overall district population with outcomes from its native population.

3.1 Basic results

Using the specification in equation (2), we evaluate the impact of the "treatment." That is, we estimate the difference in means between treatment and control groups for four outcome variables at the district level: Average per capita consumption, the poverty headcount index, the extreme poverty headcount index, and the Gini coefficient of consumption inequality across households. As mentioned in the previous section, these variables are obtained from the Peru Poverty Map corresponding to 2007.

$$Y_d = \beta_0 + \beta_1 \mathbb{I}_d[PD] + \beta_2 \mathbb{I}_d[NPDPP] + \beta_3 D_d + \beta_4 X_d + \nu_R + \nu_p + \varepsilon_d \qquad (2)$$

Equation (2) is similar to equation (1), which was explained in detail above. Here, Y_d represents a given outcome variable, X_d is a set of initial conditions, and the rest of variables are as in equation (1). Note, in particular, that the interpretation of the coefficients of interest, β_1 and β_2, depends on whether region and/or province fixed effects are included. The results are presented in Table 2.

TABLE 2. IMPACT OF MINING ACTIVITY BY 2007: BENCHMARK RESULTS
OLS: SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Across and Within Regions		Within Region		Within Province
Dependent Variable	*Producing Districts vs Districts in Nonproducing Provinces (β_1)*	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (β_2)*	*Producing Districts vs Districts in Nonproducing Provinces (β_1)*	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (β_2)*	*Producing Districts vs Nonproducing districts in the same Province (β_1)*
2007 Poverty Map					
A) Log of Average Per Capita Expenditures	0.181***	0.050**	0.132***	0.021	0.097***
	(0.044)	(0.020)	(0.039)	(0.015)	(0.037)
B) % of Population under Poverty Line	-5.880***	-2.006**	-3.117**	-0.179	-2.510*
	(1.748)	(0.899)	(1.459)	(0.750)	(1.281)
C) % of Population under Extreme Poverty Line	-3.141*	-0.035	-2.282*	0.177	-2.416**
	(1.761)	(0.966)	(1.334)	(0.818)	(1.177)
D) Gini Coefficient (%)	1.4***	0.8***	0.8***	0.5***	0.6**
	(0.4)	(0.2)	(0.3)	(0.1)	(0.3)
2007 Census					
E) % Immigrant Population	5.927***	0.168	6.672***	0.726	6.201***
	(1.400)	(0.596)	(1.398)	(0.620)	(1.360)
*Controls**					
Region Dummies	-	-	YES	YES	-
Province Dummies	-	-	-	-	YES
Observations	1,216	1,216	1,216	1,216	1,216

*All regressions include the following control variables: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). Robust standard errors are reported in parentheses below each coefficient.
*** p<0.01; ** p<0.05; * p<0.1.

Producing districts (treatment 1) have larger consumption per capita and lower poverty and extreme poverty indexes than non-producing districts, whether the latter are in the same province (treatment 2) or in a non-producing province (control). At the same time, however, producing districts have larger income inequality than non-producing districts. The differences between non-producing districts in a producing province and non-producing districts elsewhere in the same region are not significant, except for income inequality. Therefore, mining activity appears to be related to increased inequality both within producing districts and across districts in the same or other provinces.

The differences in means are larger in size and more statistically significant when comparisons are not limited to the same region or province (first two columns, labeled “Across and Within Regions”). The quality of the identification strategy improves when comparisons are restricted to districts in the same region (intermediate columns, labeled “Within Region”). Although the size and significance of the effects decline, they are arguably more reliable. The sharpest comparison is between the two treatment groups, when we restrict the comparisons to districts within the same province (last column, labeled “Within Province”). Focusing on the last set of results, producing districts have 10 percent larger per capita consumption than nonproducing districts and 2.5 percentage points less poor and extreme poor population. On the negative side, the Gini coefficient of (consumption) inequality is 0.6 percentage points larger in producing than nonproducing districts.

3.2 Robustness

To check the robustness of the results, we extend the analysis along two dimensions. First, we use propensity score matching to select comparable districts among our sample, as an alternative to controlling for initial conditions via multiple regression analysis. Second, we take into account the magnitude of mineral production, as an alternative to using a binary, dummy variable approach to characterizing districts in producing provinces.

Propensity score matching

As an alternative to using control variables in a regression setting, we use a matching procedure to select comparable producing and nonproducing districts. Specifically, we match producing districts with various subsamples of non-producing districts of similar characteristics using a propensity score built upon a probit regression. For consistency, the matching variables are the same time-invariant characteristics and initial (1993) conditions used as controls in the basic regression. In addition, to obtain the “Within Region” results we include region dummies in the set of matching variables, and similarly to obtain the “Within Province” results we include there province dummies (obviously, for the “Across and Within Regions” results, we exclude region and province dummies). We then estimate the Average effect of Treatment on the Treated (ATT) using an Epanechnikov Kernel with a bandwidth of 0.2. We obtain standard errors through bootstrapping, using 100 repetitions. The results are presented in Table 3.

The propensity score matching approach is supportive of the basic regression results. Producing districts have higher average per capita consumption and lower poverty and extreme poverty headcount indexes than non-producing districts. These results are uniformly statistically significant when comparing districts across and within regions (first column) and within the same province (last column). The results are weaker in significance when restricting the comparison to the same region (third column). On the negative side, producing districts suffer from higher inequality than any other group of districts, and this result is always statistically significant. Non-producing districts in producing provinces also suffer from higher inequality than districts in nonproducing provinces, with some evidence of higher average per capita consumption (similar but weaker in magnitude as the difference between producing districts and districts in nonproducing provinces). Focusing on the within province results, the mean differences between producing and nonproducing districts in the same province are larger in magnitude than those obtained under the basic regression but less precisely estimated.

TABLE 3. PROPENSITY SCORE MATCHING: AVERAGE EFFECT OF TREATMENT ON THE TREATED (ATT)
SUBSAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Across and Within Regions		Within Region		Within Province
Dependent Variable	*Producing Districts vs Districts in Nonproducing Provinces (β_1)*	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (β_2)*	*Producing Districts vs Districts in Nonproducing Provinces (β_1)*	*Nonproducing Districts in Producing Provinces vs Districts in Nonproducing Provinces (β_2)*	*Producing Districts vs Nonproducing districts in the same Province (β_1)*
2007 Poverty Map					
A) Log of Average Per Capita Expenditures	0.209***	0.062**	0.121**	0.040*	0.131**
	(0.064)	(0.029)	(0.065)	(0.029)	(0.067)
B) % of Population under Poverty Line	-6.839***	-2.624**	-3.459	-0.992	-3.989*
	(2.516)	(1.289)	(3.365)	(1.487)	(2.710)
C) % of Population under Extreme Poverty Line	-4.483**	-0.610	-2.917	-0.412	-3.230*
	(2.179)	(1.202)	(2.841)	(1.632)	(2.271)
D) Gini Coefficient (%)	1.4***	0.8***	1.4***	0.9***	0.9**
	(0.4)	(0.3)	(0.5)	(0.2)	(0.5)
Observations	752	1,121	685	1,050	513

The propensity score is built via a probit where each treatment group is regressed on: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). For "Within Region" estimation, region dummies are included in the set of matching variables; similarly for "Within Province" estimation, province dummies are included. Standard errors from bootstrapping with 100 repetitions are reported in parentheses below each coefficient. *** p<0.01; ** p<0.05; * p<0.1.

Magnitude of production

Producing districts do vary regarding the value of their mining production. The basic specification does not take into account this variation, and we now check whether accounting for the value of production affects the main results. For this purpose, regression equation (2) is transformed into the following,

$$Y_d = \beta_0 + \beta_1 \mathbb{I}_d[PD] * Prod_d + \beta_2 \mathbb{I}_d[NPDPP] * Prod_p + \beta_3 D_d + \beta_4 X_d + \nu_R + \nu_p + \varepsilon_d \quad (3)$$

where, $Prod_d$ is the (log of 1 plus the) accumulated value of mineral production per capita in the district between 2002 and 2006, and $Prod_p$ is the (log of 1 plus the) accumulated value of mineral production per capita in the corresponding province over the same period.[10] The results are presented in Table 4.

TABLE 4. MAGNITUDE OF PRODUCTION: IMPACT OF ACCUMULATED VALUE OF MINING PRODUCTION PER CAPITA
OLS: SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Across and Within Regions		Within Region		Within Province
Dependent Variable	*Value of Production in the District per Capita*[£]	*Dummy for Nonproducing Districts in Producing Provinces * Value of Production in the Province per Capita*[£]	*Value of Production in the District per Capita*[£]	*Dummy for Nonproducing Districts in Producing Provinces * Value of Production in the Province per Capita*[£]	*Value of Production in the District per Capita*[£]
2007 Poverty Map					
A) Log of Average Per Capita Expenditures	0.026***	0.002	0.022***	0.005*	0.016***
	(0.007)	(0.003)	(0.006)	(0.003)	(0.006)
B) % of Population under Poverty Line	-0.878***	-0.155	-0.585***	-0.163	-0.379**
	(0.227)	(0.146)	(0.197)	(0.122)	(0.190)
C) % of Population under Extreme Poverty Line	-0.716***	-0.031	-0.585***	-0.175	-0.422**
	(0.215)	(0.159)	(0.173)	(0.132)	(0.170)
D) Gini Coefficient (%)	0.2***	0.1***	0.1*	0.02	0.1*
	(0.1)	(0.03)	(0.04)	(0.02)	(0.04)
*Controls**					
Region Dummies	-	-	YES	YES	-
Province Dummies	-	-	-	-	YES
Observations	1,216	1,216	1,216	1,216	1,216

*All regressions include the following control variables: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). Robust standard errors are reported in parentheses below each coefficient.
*** p<0.01; ** p<0.05; * p<0.1.
[£] All production values (x) are measured in Soles per capita and transformed to log(1+x).

The estimation results that take into account the value of mining production confirm those of the basic specification in all relevant respects. The interpretation of the coefficients, however, is somewhat different since in this case the magnitude of mining activity matters. Larger values of mineral production in a district are related to higher average per capita consumption, lower poverty and

[10] The indicator variable $\mathbb{I}_d[PD]$in equation (3) is redundant. We include it for clarity purposes.

extreme poverty indexes, and higher inequality. The coefficient sizes are larger when comparisons between producing and nonproducing districts are across and within regions; and they get smaller as region and then province fixed effects are included, remaining however statistically significant. On the other hand (but similarly to the basic results), for non-producing districts the value of production in their province does not seem to be related to different socioeconomic outcomes, at least not on a consistent basis. Such a result may come as a surprise since higher production in a province is associated with higher *Canon* transferred to all districts in that province, and suggests a rather weak effect of the *Canon* – something that we explore below in greater detail.

3.3 Localized effects

We now study to what extent the effects of mining activity are localized; that is, whether they apply only to producing districts without spillovers to their geographic neighbors. For this purpose, in addition to using administrative jurisdictions to identify treatment and control groups, we employ a criterion based on geographic proximity. Specifically, we use mapping software to identify first-order and second and higher-order neighbors of mining districts. First neighbors share a border with producing districts, second neighbors share a border with first neighbors, and so on. (Producing districts are identified as such, and not as neighbors of other producing districts.) For this extension, regression equation (2) is transformed into the following,

$$Y_d = \beta_0 + \beta_1 \mathbb{I}_d[PD] + \beta_2 \mathbb{I}_d[First\ Neighbor] + \beta_3 D_d + \beta_4 X_d + \nu_R + \nu_p + \varepsilon_d \qquad (4)$$

Under this specification, first neighbors belong to treatment 2, and second and higher-order neighbors correspond to the control group. Note that in this case, $\mathbb{I}_d[First\ Neighbor]$ is not dropped when province dummies are included, and, therefore, β_1 and β_2 can both be estimated within provinces. This approach can be useful in two aspects. First, by focusing attention on districts that share borders and are more likely to be similar, this exercise may help address further potential omitted variable biases. Second, it allows exploration of how much geographic proximity, beyond purely administrative jurisdiction, matters for identifying the effects of mining activity. In particular, while under the basic specification all non-producing districts in producing provinces are treated as equals, the specification in equation (4) allows us to distinguish between first and higher order neighbors within the same province. The results are presented in Table 5, focusing only on the within-province comparisons.

The comparisons based on geographic proximity confirm the results of the basic specification, with support for the notion of localized effects. Producing districts have larger average per capita consumption and lower poverty rates than neighboring districts. On the other hand, producing districts also present larger inequality than neighboring districts. Moreover, producing districts are almost as different from first neighbors as they are from second and higher-order neighbors. The sizes of the coefficients measuring the mean difference between producing districts and the rest are around the same as in the basic regression. The estimated differences between first and second and higher-order neighbors are not statistically significant. These results suggest that mining effects are confined to producing districts.

TABLE 5. DIFFERENT IMPACTS ACROSS NEIGHBORING DISTRICTS

OLS: SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Within Province		
Dependent Variable	*Producing Districts vs Nonproducing Second Neighbors (β_1)*	*Nonproducing First Neighbors vs Nonproducing Second Neighbors (β_2)*	*Producing Districts vs Nonproducing First Neighbors ($\beta_1 - \beta_2$)*
2007 Poverty Map			
A) Log of Average Per Capita Expenditures	0.084**	-0.022	0.106***
	(0.042)	(0.024)	(0.036)
B) % Pop. under Poverty Line	-2.415*	0.166	-2.589**
	(1.348)	(0.741)	(1.319)
C) % Pop under Extreme Poverty Line	-1.820	0.983	-2.828**
	(1.267)	(0.818)	(1.226)
D) Gini Coefficient (%)	0.8***	0.2	0.5**
	(0.3)	(0.2)	(0.3)
*Controls**			
Province Dummies	YES	YES	YES
Observations	1,214	1,214	1,216

*All regressions include the following control variables: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). Robust standard errors are reported in parentheses below each coefficient. *** p<0.01; ** p<0.05; * p<0.1

3.4 The Canon

We now turn to analyzing the Mining Canon, with the dual purpose of evaluating its effect on poverty and inequality and checking whether including it affects the basic results of mining activity. For this purpose, regression equation (4) is augmented as follows,

$$Y_d = \beta_0 + \beta_1 Prod_d + \beta_2 \mathbb{I}_d[NPDPP] * Prod_p + \beta_3 D_d + \beta_4 X_d + \beta_5 * Canon_d + \nu_R + \nu_p + \varepsilon_d \quad (5)$$

where, $Canon_d$ is the (log of 1 plus) the accumulated value of government transfers during 2002-2006, made in accordance to the Mining Canon Law of 2002 and its addendums. Regression equation (5) cannot be estimated directly by OLS because Canon transfers are jointly endogenous with the dependent variables. In fact, the Canon's distribution rule (for district, province and region allocations) factors in socioeconomic indicators that are closely connected with income, poverty, and inequality measures.

We use an instrumental variable (IV) procedure to deal with the endogeneity of the Canon. We construct an instrument based on a revenue distribution rule that takes into account the district's jurisdictional location and population, while abstracting from other socioeconomic characteristics. Thus, the instrument considers the revenue shares mandated by law according to the location of production (district, province, and region) and population weights. Since 2002, there have been 3 revenue distribution regimes (corresponding to the original canon law and its 2 subsequent modifications). They respectively apply to: 2002-03, 2004, and 2005-present. The instrument is built by following the specific rules of the corresponding regime per year and then accumulating for the period 2002-06. This is done both in total and per capita terms, resulting in 2 instruments. Since only overall revenues at the regional level could be obtained directly from the data, we used the assumption that province and district revenues were proportional to their respective value of mining production. Table 6 presents the results obtained with the IV procedure and, for comparison purposes, the OLS results. We focus on the within-province exercise.

TABLE 6. IMPACT OF ACCUMULATED VALUE OF MINING PRODUCTION AND MINING CANON PER CAPITA

SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXLUDING LIMA)

	Within Province				
	OLS		INSTRUMENTAL VARIABLES[££]		
Dependent Variable	*Value of Production in the District Per Capita*[£]	*Value of Mining Canon per Capita*[£]	*Value of Production in the District per Capita*[£]	*Value of Mining Canon per Capita*[£]	*Sargan Test of Overidentifying Restrictions (p-value)*
2007 Poverty Map					
A) Log of Average Per Capita Expenditures	0.020***	-0.072***	0.019***	-0.060	0.3486
	(0.006)	(0.026)	(0.005)	(0.089)	
B) % of Population under Poverty Line	-0.528***	3.105***	-0.416*	1.299	0.2995
	(0.192)	(1.171)	(0.247)	(3.157)	
C) % Pop under Extreme Poverty Line	-0.507***	1.758	-0.256	-3.110	0.3115
	(0.175)	(1.102)	(0.239)	(3.143)	
D) Gini Coefficient (%)	0.1**	-0.5**	0.1**	-0.4	0.2515
	(0.0)	(0.2)	(0.0)	(0.7)	
*Controls**					
Province Dummies	YES	YES	YES	YES	
Observations	1,216	1,216	1,216	1,216	

*All regressions include the following control variables: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). Robust standard errors are reported in parentheses below each coefficient. *** p<0.01; ** p<0.05; * p<0.1.

[£] All production and canon values (x) are measured in Soles per capita and transformed to log(1+x).

[££] The instrumental variables are constructed following the Mining Canon revenue distribution rule, taking into account the district's jurisdictional location and population but abstracting from other socioeconomic characteristics (such as poverty rates). Further details on the instruments are provided in the main text.

Taken at face value, the OLS results suggest a significant association between larger Canon transfers and worse socioeconomic conditions: lower average per capita consumption and higher poverty headcount index. This likely reflects the fact that the Canon allocation gives more to districts that are more in need. In fact, the IV results confirm that the negative OLS results are due to reverse causation: Once instrumented, the Canon does not seem to have a detrimental effect on districts' per capita consumption and poverty.[11] However, it does not appear to have a beneficial impact either. This is an interesting and important topic and deserves further research study.

Finally, the coefficients on the value of mining production retain their sign and significance after the Canon transfer is included (except for extreme poverty headcount index). This, together with the

[11] The instruments seem to perform well statistically, with acceptable Hansen/Sargan specification tests.

lack of Canon effect, suggests that the socioeconomic impact of mining is related to the economic activity itself, rather than the fiscal revenues it generates.

3.5 The mechanism: migrants or natives?

Our analysis uses the district as the unit of observation. This is not only due to data limitations but also to our concern for understanding outcomes at the community level. Districts are not, however, homogenous entities, and aggregate local effects may mask differing impacts on the population. Of particular interest to understand the mechanism of mining effects is the difference between migrant and native populations. The poverty map does not have information at the household level, so that studying the disaggregated effects on consumption and poverty by groups within a district is not feasible. Census data can, however, shed light on our results.

The 2007 Census allows distinguishing between native and immigrant populations. It reports whether the mother of a respondent living in a district was a resident of the same district when the respondent was born. If this is the case, we identify the person as native, and otherwise as immigrant.[12] Then, the first question to address is whether there are significant differences across districts regarding immigration. The results are reported at the bottom of Table 2. Producing districts have larger immigrant populations than non-producing districts in the same province or in other, non-producing, provinces. In fact, the share of immigrants in the total population is over 6 percentage points higher in producing than nonproducing districts.

This raises the question of whether the better consumption and poverty outcomes observed for mining districts are due to their having wealthier and more educated immigrants. To address this question we compare educational and labor indicators for total and native populations. We present only the mean differences between producing and nonproducing districts in the same province (for which identification is arguably the most precise).[13] The results, presented in Table 7, are remarkable. The educational differences observed for the whole population are driven by immigrants' characteristics: Producing districts have better educational indicators than nonproducing districts because of their well-educated immigrants, not because of differences across native populations. On the positive side, native populations in producing districts do have a larger share of salaried workers than native populations in nonproducing districts.

[12] The results are robust to other criteria for identifying native population; for instance, whether the head of household has lived in the district for more than five years.

[13] The results are similar for comparisons between producing districts and districts in nonproducing provinces (treatment 1 vs. control).

TABLE 7. EDUCATIONAL AND EMPLOYMENT DIFFERENCES ACROSS NATIVE AND IMMIGRANT POPULATIONS
OLS: SAMPLE OF ALL DISTRICTS IN PRODUCING REGIONS (EXCLUDING LIMA)

	Producing Districts vs Nonproducing Districts in the Same Province (β_1)		
Dependent Variable	*Native Population*[£]	*Immigrant Population*	*General Population*
2007 Census			
Population older than 15 years old			
A) % of Population that is Illiterate	-0.321	-3.322***	-1.695***
	(0.341)	(0.568)	(0.484)
B) % of Population with Less Than Primary Education	-0.430	-3.352***	-1.276***
	(0.396)	(0.636)	(0.389)
C) % of Population with Primary Education	-0.621	-4.526***	-1.474***
	(0.582)		(0.535)
		(0.905)	
D) % of Population with Secondary Education or Above	1.016	10.099***	4.111***
	(0.873)	(1.437)	(0.924)
E) % of Population with Paid Work at the Time of Census	3.656***	9.900***	6.468***
	(1.196)	(1.545)	(1.295)
*Controls**			
Province Dummies	YES	YES	YES
Observations	1,216	1,216	1,216

* All regressions include the following control variables: Provincial Capital Dummies; Log of Area; Log of Altitude; Log of Population in 1993; % of Rural Population in 1993; % of Household with Water Supply in 1993; % of Household with Electricity in 1993; % of Illiteracy in 1993 (population older than 15 years old); % of Population with Paid Work at the Time of Census in 1993; Log of Accumulated Foncomun Transfers Per Capita in Soles (2002-2006). Robust standard errors are reported in parentheses below each coefficient. *** p<0.01; ** p<0.05; * p<0.1.
[£] Native populations are identified based on the following question in the 2007 Census: "When you were born, was your mother a resident of this district?"

These results suggest that the better *average* outcomes enjoyed by producing districts are in part explained by the well-educated (and presumably well-paid) immigrants that mining activities require and attract. To some extent, this may explain not only the better outcomes regarding consumption per capita and poverty headcount index but also the worse outcomes regarding inequality. We should not, however, ignore the positive impact of mining on the salaried employment of natives: some of them, presumably the more qualified, seem to get jobs in mining and related economic activities.

4. Conclusions

Mining has a dual impact on local communities in Peru: It has a positive *average* effect but a negative *distributional* effect. On the positive side, producing districts have 10 percent larger per capita consumption than comparable nonproducing districts and 2.5 percentage points less poor and extreme poor population. On the negative side, the Gini coefficient of inequality is 0.6 percentage points larger in producing than nonproducing districts. Moreover, the positive average benefits are limited to producing districts, with no discernable spillovers to other districts even in the same province. Mining, therefore, appears to lead to higher inequality both within and across local communities.

Mining's dual effect is partly explained by the well-educated (and presumably well-paid) immigrants that mining activities require and attract to producing localities. It is also explained by the jobs that some community natives (presumably the more qualified) are able to get in industries and services related to mining activity. The distributional impact of mining may explain, at least in part, the social discontent regarding mining activities in the country.

The paper highlights some areas for future research. The first has to do with understanding the connection between social conflict and natural resource extraction. We have underscored the importance of economic distributional effects. However, capture of rents by local politicians, concerns about environmental damage, and cultural alienation of native populations, to name a few, may also be relevant explanations.

The second area for future research is regarding the usefulness of fiscal transfers to local governments. In principle these transfers can fund public goods and services that increase welfare in local communities and counteract any negative impacts derived from mining activity. We find neither a detrimental nor a beneficial effect from the Mining Canon in Peru. One possibility is that by 2007 it was too soon to obtain any significant effects from a decentralization program that had been working for 5 years. Another possibility is that decentralization in Peru is flawed and must be restructured, decreasing the incentives for corruption and capture of local governments and improving their managerial and implementation capacity.

Solving the social discontent with mining and allowing it to reach its potential may require a broader discussion and overarching institutional reforms: Should people in local communities be made co-owners of mining companies, by distributing among them stockholder rights and dividends? Should the management of mining revenues be only one component, albeit essential, in a comprehensive reform of fiscal decentralization in Peru?

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APPENDIX TABLE A1. VARIABLES DEFINITIONS AND SOURCES

	Type	*Source*
Outcome Variables		
Average Per Capita Monthly Consumption Expenditures in 2007 (Soles)	2007 Poverty Map	National Statistical Institute (INEI)
Poverty headcount index: Percent of Population under Poverty Line in 2007 The poverty line is the minimal amount of money needed by an individual to buy goods and services to satisfy basic needs. The poverty line varies by Region and urban/rural geographic areas.	2007 Poverty Map	National Statistical Institute (INEI)
Extreme poverty headcount index: Percent of Population under Extreme Poverty Line in 2007 The extreme poverty line is the minimal amount of money needed by an individual to satisfy basic food needs The extreme poverty line varies by Region and urban/rural geographic areas.	2007 Poverty Map	National Statistical Institute (INEI)
Gini Coefficient of Consumption Expenditure in 2007	2007 Poverty Map	National Statistical Institute (INEI)
Regressors		
1993 Control Variables	1993 Census	National Statistical Institute (INEI)
Producing Districts Dummy variable that takes the value of one for all districts where there was (tax paying) production of any mineral (mainly copper, gold, and silver) between 2002 and 2006	Administrative Data	Peruvian Ministry of Energy and Mining (MINEM)
Nonproducing Districts in Producing Provinces Dummy variable that takes the value of one for Non-Producing Districts in a province where there is at least one Producing District.	Administrative Data	Peruvian Ministry of Energy and Mining (MINEM)
Districts in Nonproducing Provinces Dummy variable that takes the value of one for Non-Producing Districts in a Non-Producing Province in a Region where there is at least one Producing District.	Administrative Data	Peruvian Ministry of Energy and Mining (MINEM)
Value of Mineral Production in Producing Districts Accumulated value of mineral production by all mining facilities within a district for the period 2002-2006. Quantity of mineral production is reported annually by the Ministry of Energy and Mining (MINEM). Mineral prices are the annual average dollar prices per mineral reported by MINEM. Dollar values are converted into Peruvian Soles using average exchange rates, then divided by the CPI to adjust for inflation, and finally added over 2002-06.	Administrative Data	Peruvian Ministry of Energy and Mining (MINEM)
Value of Mineral Production in Producing Provinces Sum of the value of production across all districts in a producing province for 2002-2006 in (constant price) Soles.	Administrative Data	Peruvian Ministry of Energy and Mining (MINEM)
Foncomun Accumulated revenues from the Foncomun for 2002-2006 in (constant price) Soles.	Administrative Data	Peruvian Ministry of Economy and Finance (MEF)
Mining Canon Accumulated revenues from the Mining Canon for 2002-2006 in (constant price) Soles.	Administrative Data	Peruvian Ministry of Economy and Finance (MEF)

APPENDIX TABLE A2. SUMMARY STATISTICS

COMPARISON OF MEANS OF OUTCOME VARIABLES AND REGRESSORS BY GROUPS (Standard deviations in parentheses)

	(1) *Producing Districts*	(2) *Nonproducing Districts in Producing Provinces*	(3) *Districts in Nonproducing Provinces*
Outcome Variables			
Average Per Capita Monthly Expenditures in 2007 (Soles)	333.63 (491.30)	280.34 (1,203.48)	210.57 (109.60)
% of Population under Poverty Line	55.47 (22.83)	62.49 (21.03)	64.44 (21.67)
% of Population under Extreme Poverty Line	25.67 (20.31)	31.37 (20.74)	31.75 (19.73)
Gini Coefficient (%)	30 (4)	29 (4)	28 (4)
Regressors			
Altitude (meters)	2,880.02 (1,156.47)	2,913.34 (910.51)	2,621.93 (1,203.71)
Area (square kilometers)	627.24 (817.18)	396.12 (712.49)	434.46 (1,184.59)
Provincial Capital Dummy	0.10 (0.30)	0.09 (0.29)	0.11 (0.32)
Log of Population in 1993	8.44 (1.13)	7.92 (1.07)	8.44 (1.07)
% of Rural Population in 1993	59.30 (30.39)	61.19 (27.15)	65.70 (28.36)
% of Household with Water Supply in 1993	20.01 (20.90)	20.03 (20.23)	18.49 (20.86)
% of Households without Electricity in 1993	69.56 (29.66)	79.25 (25.56)	76.87 (27.78)
% of Population that is Illiterate in 1993 (population older than 15 years old)	22.16 (12.61)	25.29 (12.89)	26.88 (13.56)
% of Population with Paid Work at the Time of Census in 1993	29.54 (8.57)	27.49 (7.99)	26.92 (6.90)
Accumulated Mineral Production per Capita in District in Soles (2002-2006)	13,224.35 (36,424.94)	0.00 (0.00)	0.00 (0.00)
Accumulated Foncomun per Capita in Soles (2002-2006)	657.01 (468.36)	905.51 (691.97)	730.16 (700.61)
Accumulated Mining Canon per Capita in Soles (2002-2006)	694.25 (1,923.64)	432.79 (1,317.90)	180.27 (339.44)
Observations	89	462	665