Global boom, local impacts

Mining revenues and subnational outcomes in Peru 2007-2011

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Abstract

The relationship between the abundance of natural resources and socio-economic performance has been a main object of study in the economic development field since Adam Smith. Dominated by the verification of the so called *curse of natural resource,* the mainstream literature on the topic has been mostly on the study of cross sectional data at the national level, with limited empirical use of exogenous differences in the abundance of natural resources at the subnational level. We explore the case of Peru, a mining-rich middle income country where -exploiting a unique data set constructed for this purpose- we are able to assess systematic differences in district-level welfare outcomes between mining and non-mining districts. We find evidence that the condition of being mining-abundant district have a significant impact on the pace of reduction of poverty rates and inequality levels. We also estimate a heterogeneous response to the mining-abundant condition, finding stronger responses in lower-poverty, higher-inequality districts. Finally, we find a trend suggesting incremental positive marginal effects of the level of exposure to mining transfer, as proxy for the "degree" of abundance of mining activities, on the reduction of poverty and inequality.

1. Introduction

While the notion of abundance of natural resources as being related to countries' anemic economic performance has been object of study since Adam Smith, it was only since the 1990s when a wave of cross national studies empirically confirmed the relationship between natural-resource abundance and slower economic growth. This kind of relationship was baptized –somehow pompously- as the curse of the natural resources.

However, the same literature that confirms this curse-type empirical regularity, offers remarkably less agreement on the mechanics of the transmission mechanisms of such curse. Since the influential seminal work by Sachs and Warner (1995 and 2001), many empirically-tested explanations has been attempted in the literature.

With no pretention of being exhaustive, one can attempt a taxonomy of potential causes of the curse, where usual suspects are bureaucratic efficiency issues, governance problems, tendency to delay needed reforms, rent-seeking, and even institutional weaknesses inherited from colonial origins. Sachs and Warner themselves, along with works by Mehlum *et al* (2006), Zambrano (2008), Kronenberg (2004), Auty (2000) and Ross (1999), among many others, contributed to this line of thought.

Other set of studies points towards distortions in the accumulation of productive factors, including under-investment in human capital and crowding-out effects in education like in Gylfason (2001b), Kronenberg (2004), and Papirakys and Gerlagh (2004); and also capital over-accumulation like in Rodríguez and Sachs (1999). There are also the more traditional explanations linking natural resource abundance and decreasing manufacturing exports and other variants of the Dutch disease including, for example, Papirakys and Gerlagh (2004); Gylfason(2001), Sachs and Warner (1995) and, van Wijnbergen (1984).

A set of alternative works points out the role of other economic factors, like the debt overhang and failure in the macroeconomic management (Manzano and Rigobón, 2001); the decay of general quality of economic and institutional management (Gylfason, 2001); and the degree of economic openness (Papirakys and Gerlagh, 2004). Another empirical regularity is that countries with abundant natural

resources tend to be exposed to a higher degree of external volatility and present higher degree of pro-cyclicality in their economic policies, and therefore are more prone to unsustainability and insolvency[1].

Most of the literature on the resource curse –in favor or against it- is empirically based on cross sectional data at the national level. To some extent, this methodological approach could be prone to identification problems due to endogeneity and omitted variable bias arising from non-observable factors that could simultaneously influence the performance/outcome variable and the independent variables. As mentioned by Loayza *et al* (2012), notwithstanding their contribution, cross-country studies "have suffered from uneven data quality and limited treatment of omitted variables that may correlate with resource abundance".

What is not really frequent in the curse-related literature is the use of cross sectional data at subnational-level. Arguably, differences in the abundance of natural resources among different geographical or political units *within* the same country could, at least potentially, offer a source of exogenous variance that can be advantageous for identification purposes. By sharing the same national, institutional/legal framework, cultural, demographic features, and facing the same international environment, data from subnational level could validate some of the curse-induced potential problems, without the bias arising from a cross-country setting.

For that purpose this paper explores the case of Peru, a middle-income country abundant in natural resources –mostly mining-, who has greatly benefitted from the recent boom in commodity prices. Peru´s legal framework –particularly since the enacting of the *Canon Minero Law* of 2004- includes distributional rules that –in general terms- create systematic differences in the level of fiscal revenues between producing and non-producing districts, with only limited compensatory fiscal transfers for non-producing municipalities[2].

We find evidence that being a mining district have a significant impact on the pace of poverty reduction and inequality comparing with non-mining districts. In fact, our results show that, during the period

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[1] On the other side of the spectrum, there are some findings that suggested there is not such effect like a curse-type relationship between natural resources and economic performance. For example, Brunnschweiler and Bulte (2008) argue that the curse vanishes when looking not at the relative importance of resource on exports, but rather the relative abundance of natural resources deposits under the ground. They found that resource richness correlates with slightly higher economic growth and slightly fewer armed conflicts. Cavalcanti *et al* (2011) challenge the methodologies that empirically show that oil abundance is a curse, and found that oil abundance positively affects both short-term growth and long-term income levels. Finally, Litschig (2008) found that local officials may handle revenues from commodity extraction differently than other transfers from the central government, which do seem to positively affect human capital and reduce poverty.

[2] See section 2 for further details on mining revenues distribution rules and other features of the fiscal regime in Peru.

2007-2011, mining districts experience a reduction in poverty 2.65 percentage points per year higher than non-mining ones. Likewise, mining districts cut inequality by 1.3 points per year more than non-mining ones. Among mining districts, we find stronger responses in initially lower-poverty, higher-inequality districts, while we also find differential response to *dosage* of the treatment, including a trend suggesting incremental marginal effects on the selected outcomes of our measure of "intensity of mining abundance" –proxied by the relative size of fiscal revenues from mining-.

This paper is organized as follows. Section 2 put some context into the discussion of the Peruvian case, by characterizing the importance of the mining industry for its economic performance. This section also describes in greater detail the Peruvian mining-specific taxing/distribution rules, particularly the *Canon Minero*. Section 3 describes the data sets used in this study; Section 4 discusses the empirical strategy used for identification of the impact of mining revenues over socioeconomic outcomes at the district level in Peru. Section 5 presents the results of the different approaches and analysis, and Section 6 lays some final remarks.

2. Context

Peru is a small open economy with abundance of natural resources. Peru not only produces large amounts of mining products (gold, copper, silver, tin, zinc, iron, lead and zinc), but also fishery (fishmeal and fish oil), agricultural products (coffee and sugar) and oil and natural gas. Mining, by far the largest extractive activity in Peru, has been a very dynamic sector in the last decade, becoming the driver of investment and one of the main determinants of its external and fiscal accounts. This sector represents approximately 4.2% of GDP, employing directly 1.4% of the labor force, and generates large foreign direct investment inflows that amounted 4.6% of GDP only in 2012.

According to the National Constitution of 1993 (Art. 66), the State owns the mineral resources and delegates extractive mining activities to the private sector under concession contracts. The sector is subject to a special tax scheme to extract rents from private operators, which are then distributed to different levels of government, including a large portion directed to local governments in mining extraction districts.

Due to the combination of large investments in exploration and production, and explosive growth in international mineral prices, mining exports grew from US$4.7 billion to US$25.9 billion between 2003

and 2012. During this period, mining exports grew to represent about 60% of total exports from 45% a decade ago.

At the same time, the mining sector has become an increasing source of revenue for public coffers, being subject to a 30% - 32% income tax on the gross income of operating companies. Mining is also subject to a 4.1% tax on dividends and, to lesser extent, to general VAT and imports taxes. On top, 1% to 3% royalty fee is also applied on gross sales of mining[3,4].

Under this fiscal regime, and propelled by prices, mining tax procedures grew from 4.2% of total tax revenue in 2000 to 17.5% in 2011. Total mining revenue –tax and nontax- went from 2.5% to 14.0% of total Central Government current revenue in the same period.

Since 2001, with the beginning of fiscal decentralization process in Peru, natural-resource revenues have gained importance as a source of income not only for the Central Government, but also for subnational governments as well. In 2004 the *Canon Minero Law*[5] regulated the arrangement by which subnational governments shared a portion of the total income obtained by the economic exploitation of mineral resources. Although enacted in 2004, full implementation of the *Canon Minero Law* did not begin until 2006, and its effects were fully noticeable in 2007.

As shown in Figure 1, transfers from the Central Government to subnational entities increase exponentially in 2007, under the effect of the of *Canon Minero* and the spike of international commodities prices. Between 2007 and 2012, the amount of transfers was twelvefold the average from the previous ten years. In the side of non-tax revenue, being related directly to the export prices of mineral products, mining royalties experienced similar behavior.

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[3] Since 2011, Peru modified its mining royalty regime to variable income scheme. They created a special windfall tax in addition to changes in the basis of calculation of royalties that passed from gross sales to a notion of operational profits. The applicable rates for both royalties and windfall tax are set according to a sliding scale according to the size of the operating margin. Depending on the operating margin and tax regime, stable or not, the excise tax on profit margin ranges from 2% to 13.4%, while royalties range from 1% to 12%.

[4] For a more detailed account of the Peruvian mining fiscal regime see: Del Valle, M (2013), Ingresos fiscales provenientes de la explotación de recursos mineros e hidrocarburos en Perú. IADB Mimeo.

[5] There is also a distribution framework for the revenue coming from oil and gas, fishery, forestry and hydroelectric exploitations; however the *Canon Minero* is by far the largest and most relevant source of subnational transfers of them all.

Figure 1
Evolution of *Canon Minero* transfers to subnational levels.
Peru 1996-2012

Million of Nuevos Soles of 2012

Source: Ministry of Economy and Finance
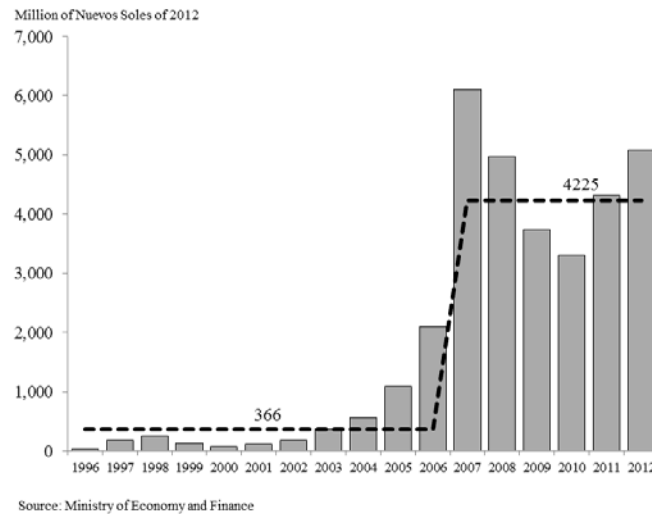
Peru is divided in 25 Regions, 195 Provinces and 1.839 districts. Districts, the lower political and administrative level of government, are usually sparsely populated with an average population of 15.000 inhabitants (lowest in LAC), 90% of them with 20.000 inhabitants or less (Vega, 2008). Districts in Peru do not collect directly mining revenues. Total mining revenues in hands of districts in Peru are the sum of the transfers from the Central Government of *Canon Minero,* build from the 50% of the income taxes paid by mining companies; and mining royalties, which are directed entirely towards subnational entities. Transfers of *Canon Minero* and royalties to local governments grew from US$100 million in 2004 to US$ 2.5 billion in 2012[6].

The distribution of *Canon Minero* involves a two-step process as follows: 10% of the Canon goes directly to the producing district; 25% is divided among the districts of the province the producing district; 40% is divided between the districts of the department of the producer district; and the remaining 25% goes to the regional government, of which 20% goes to National Universities under its jurisdiction. The second step sets a distribution mechanism within each portion, gives greater shares to those subnational entities based on a population and poverty rule. Similarly, mining royalties are distributed as follows: 20% for the producing district; 20% is divided among district of the province of

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[6] To illustrate the importance of this source of revenue for sub national entities in Peru, only in 2012 mining transfers accounted for more than 28.7% of total current revenues of local governments (versus only 6.4% in 2004). Also *Canon Minero* was the source of 36% of total public investments at the local level in 2012.

the producer district; 40% is divided among districts of the department of the producer district; 15% goes to the regional government; and 5% goes national universities under the jurisdiction. In a second step, a distribution mechanism considering population and poverty is used[7].

As mentioned, the application of such legal framework has implied that fiscal rents –tax and nontax- directed to the lower level of government has grown more than twelve-fold in recent years. Characteristic of this regime is that transfers to non-producing territories for territorial equity considerations are inexistent. This is an important feature of the Peruvian mining revenues distribution rules: mineral endowment or proximity to it -and ultimately geology- is the sole determinant of this extra income stream at the district level[8]. Figure 2 illustrates the uneven distribution and relative importance of fiscal mining income at the district level in Peru between 2007 and 2011.

Figure 2
Peru: Total mining transfers as a proportion of total fiscal revenue.
District level (%)
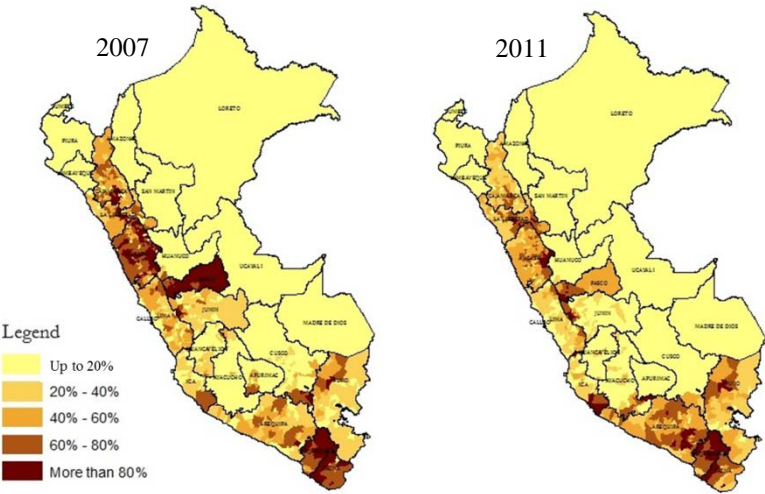
As mentioned, the issue of the local impacts of resource-related production/revenues has been gaining traction as an object of research in recent years. For example, Besfamille *et al* (2012) found differentiated behavior at the provincial level in Argentina, where local public expenditure usually

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[7] The use of both, canon and royalties, is constraint by law to finance or co-finance productive investment projects aimed to expand access to public services and generate benefits to the community, in line with national policies.
[8] This feature - the random distribution of mineral deposits over the territory- and the fact that being entitled to *Canon Minero* can be considered exogenous to district characteristics will be central for the empirical strategy of this paper.

overreacts to variations in federal transfers, while there is evidence of smoothing revenues from mining royalties. Caselli and Michaels (2011) and Gelemur and Pochat (2011), for the cases of Brazil and Argentina respectively, find no evidence of the extra stream of oil revenues to municipalities having any effect –other than higher spending- on the provision of public goods or other policy/welfare outcomes.

In the case of Peru, Arreaza and Reuter (2012) , using a difference-in -difference approach, find a positive impact on the level of spending, but no significant differences in terms of public goods provision across recipient and non-recipient districts.

Loayza *et al* (2012) uses data on geo-location of mining production –instead of fiscal revenues- and find that mining activity has a positive impact on per capita income/consumption, lowers poverty and unmet households basic needs, and improves literacy rates. They conclude that producing districts have substantially better socioeconomic outcomes than their neighbors. They also find evidence that mining production increase inequality not only across but also within producing districts. Interestingly enough, they also attempt to isolate the impact of the *Canon Minero* at the district-level, but no significantly different socioeconomic outcomes between recipients and non-recipients districts emerge.

Finally, Aragón and Rud (2013) study the local economic impact of the second world largest gold mine - Yanacocha in Northern Peru – and detect positive spillovers at the local level due to the impact of local inputs demand on real income. This result emphasizes the importance of productive linkages from extractive activities to create positive spillovers.

3. Data

Data used in this paper is constructed from six different databases collected from four different government branches. First, we use the National Household Survey (ENAHO, in Spanish) an annual survey representative at national and regional level. Household characteristics, living conditions, income, education and other variables are collected by the National Institute of Statistics (INEI).

Central for this analysis was the use of the ENAHO survey, alongside the micro data set of the National Census conducted in 2007, to estimate the set of socioeconomic outcomes at the district level for the period of interest[9]. Three outcomes at the district level were considered in this paper: poverty incidence,

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[9] For that purpose we apply the Poverty Mapping Software developed by the World Bank (POVMAP). See annex I for more detailed in the procedure in this paper to obtain district level socioeconomic data for the impact evaluation analysis.

extreme poverty incidence and inequality of the consumption distribution (Gini coefficient). For 2007 these outcomes were produced by the INEI (2009) and for 2011 and 2012, we estimate them using a methodological procedure to obtain comparable data (Elbers *et al* 2003).

This study also benefited from the National Municipality Records (RENAMU, in Spanish), which is a self-reported municipal census conducted annually since 2004[10]. Complete data on expenditure and revenues –including mining transfers- at the district level was obtained from the Ministry of Economics and Finance of Peru (MEF)[11]. We also obtained data from the National System of Public Investments (SNIP), which has information about all public investment projects presented for approval from the local government level[12].

For additional controls, INEI provided us with a geographical and demographic database with surface information, maximum and minimum altitude per district, estimates of population and number of households, and natural region characterization per district from 2007 to 2012.

4. Empirical Strategy

Our empirical strategy will be based in two assumptions. First, being linked to the location of the mining activity, and in the absence of formal distributional compensation to non-producing districts, receiving mining transfers is a process naturally random as geology itself. Also, receiving mining transfers is a proxy of being a mining district –or being a district in the proximity of a mining activity-.

The second assumption is the postulation of a potential outcomes framework, where for each district i, for i = 1, …, N, there are two potential outcomes, denoted by $Y_i(0)$ and $Y_i(1)$. The first term, $Y_i(0)$, denotes the outcome that would be realized by district i if had not received any transfers from the mining

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[10] It is compulsory for all province and district municipalities in Peru and provides diverse information of municipality characteristics such as infrastructure, assets, number of employees as well as other relevant variables. RENAMU also compiles municipality's lacks and needs in terms of project execution; project design, planning and execution capabilities; reporting of budgetary allocations; among other municipal characteristics. 1834 out of 1838 municipalities successfully completed the RENAMU census in 2011.

[11] Data on subnational government revenues and expenses were put together to form a panel from 2007 to 2011. This data also allows us to construct variables regarding percentage of revenues that come from mining activities from within the district, province or region, as well as to compare revenue growth within this period and their budget execution. Information was available for a total of 1832 subnational government revenues in 2011.

[12] The richness of the SNIP database is that it contains information on the stage of the investments projects as well as if either the project has been declared viable or not. Individual project information can be aggregated at municipal and indicators of efficiency and characteristics of municipal administrations, such as project approval ratio, type of project presented and average size of projects, can be easily constructed.

activity. Similarly, $Y_i(1)$ denotes the outcome that would be realized by district i after receiving mining transfers[13].

If it is true that the probability of receiving mining transfers is independent from any observable characteristics of the recipient districts, then we can use the common definition of causal effect at the district level as the difference $Y_i(1) - Y_i(0)$. It is important to point out that one and only one of these two potential outcomes can be realized, and they are mutually exclusive. To sum up, in this setting of N Peruvian districts, $N_1 < N$ naturally endowed districts –and its close neighbors- will be the treatment group, the remaining $N_0 = N - N_1$ non-mining districts the control group, the treatment will be the amount of mining transfers received between 2007 and 2011, and the potential outcomes will be a set of district-level income/expenditure measures estimated for this purpose.

Given this setting, the difference in difference (DID) approach will be our preferred method for inference of the average effect of the treatment. In the simplest setting, mining districts are exposed to treatment (mining transfers), while not-producing districts are not. In a two period setting, the average gain over time on non-mining districts is subtracted from the gain over time of mining districts. DID estimation removes biases in second period comparisons that could be the result from permanent differences between those groups, as well as biases arising from time trends unrelated to the mining transfers[14]. Our basic model for the DID approach follows the one discussed in recent literature by Imbens and Wooldridge (2009):

District *i* belongs to a group $G_i \in \{0, 1\}$, where group 1 is the mining endowed group. Each district belonging to each group is observed in time period $T_i \in \{0, 1\}$. The outcome for district *i* in the absence of mining transfers, $Y_i(0)$ can be written as:

$$Y_i(0) = \alpha + \beta T_i + \gamma G_i + \varepsilon_i \quad (1)$$

Where α, β, and γ are unknown parameters. The second coefficient in this specification, β, represents the time component common to both groups. The third coefficient, γ, represents a group-specific, time-

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[13] A third assumption will be that the treatment –mining transfers- received by one district do not affect outcomes for another district. It is difficult to rule out this kind of interaction effects between districts, with migration and other factors knowingly taking effect during the observed period, but addressing methodologically this concern would exceed the scope of this paper. If this interaction effects happen to be important, the estimates of this approach will be considered a lower bound of the actual effect, if the actual estimation of the impact is rather large, then the lower bound become critically informative.

[14] The DID approach assumes that, in absence of the mining transfer, temporal trends in outcomes across receiving and non-receiving districts would be the same.

invariant component. The fourth term, ε_i, represents unobservable characteristics of the district. This term is assumed to be independent of the group indicator and have the same distribution over time, i.e. orthogonal errors with mean zero.

The equations for the outcomes at the district level with and without the mining transfers are combined:

$$Y_i(1) = Y_i(0) + \tau_{DID} \quad (2)$$

Where the standard DID estimand τ is under this model equal to:

$$\tau_{DID} = E[Y_i(1)] - E[Y_i(0)] \quad (3)$$

$$\tau_{DID} = \left(E[Y_i \mid G_i=1,T_i=1] - E[Y_i \mid G_i=1,T_i=0]\right)$$

$$-\left(E[Y_i \mid G_i=0,T_i=1] - E[Y_i \mid G_i=0,T_i=0]\right) \quad (4)$$

This is the population average difference over time in the control group subtracted from the population average difference over time in the treatment group. Then we can estimate τ_{DID} simply by using OLS method on the regression function for the observed outcome:

$$Y_i(0) = \alpha + \beta_1 T_i + \gamma_1 G_i + \tau_{DID} CANON_i + \varepsilon_i \quad (5)$$

Where the treatment indicator $CANON_i$ is equal to the interaction of the treatment group and time indicators, and therefore the mining transfer effects on district outcomes is estimated through the coefficient on the interaction between the indicators for the second time period and the treatment group. This leads to:

$$\hat{\tau}_{DID} = (\bar{Y}_{11} - \bar{Y}_{10}) - (\bar{Y}_{01} - \bar{Y}_{00}) \quad (6)$$

Where:

$$\bar{Y}_{gt} = \Sigma_{i \mid G_i=g,T_i=t} \left(\frac{Y_i}{N_{gt}}\right) \quad (7)$$

Is the average outcome among districts in group g and time period t.

For a matter of robustness, we also compare how outcomes differ for mining districts relative to observationally similar non-mining districts by using a *Propensity-score matching* (PSM) methodology.

By using PSM we were able to match control and treatment groups in the base of a set of observable characteristics[15]. Formally, our PSM model will be based on the probability for a single district to receive mining transfers given observed covariates. In a setting with a binary treatment T, an outcome Y, and a vector of observable covariates X. The propensity score is defined as the conditional probability of treatment given background variables:

$$p(\chi) = \Pr(T = 1 \mid X = \chi) \quad (8)$$

Let Y(0) and Y(1) denote the potential outcomes under control and treatment groups, respectively. Then treatment assignment is (conditionally) un-confounded if treatment is independent of potential outcomes conditional on X. This can be written compactly as:

$$T \perp Y(0), Y(1) \mid X \quad (9)$$

Where ⊥ denotes statistical independence. If un-confoundedness holds, then:

$$T \perp Y(0), Y(1) \mid p(X) \quad (10)$$

We first estimated the propensity score using the psmatch2 routine by Leuven and Sianesi (2003). The approach allowed us to construct a base model including all relevant covariates at the district level, given the dichotomous nature of the condition of being a mining-transfer recipient. After calculating the propensity score, we compared the districts in one group with the matched comparison cases. We then used a nearest neighbor matching algorithm with replacement as a base case, adjusting to caliper estimation to robust the quality of the matching. In the many-to-one (radius) caliper matching with replacement, the estimator of *Canon Minero* impact may be written as:

$$E(\Delta Y) = \frac{1}{N}\sum_{i=1}^{N}\left[Y_{1i} - Y_{0j(i)}\right] \quad (11)$$

Where $Y_{0\,j(i)}$ is the average outcome for all comparison individuals who are matched with case i, Y_{1i} is the outcome for case i, and N is the number of treated cases.

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[15] Following Heinrich *et al* (2010), the PSM technique allowed us to reduce the matching problem to a single dimension: the probability that a unit in the combined sample of treated and untreated units receives the treatment, given a set of observable covariates. In our case, we use a set of cofound variables at the district level, including socio-economic, demographic and geographic information to produce valid matches for estimating the impact of receiving a stream of mining transfers between 2007 and 2011. In this context, the PSM strategy is plausible since we do have a comprehensive set of observable covariates at the district level for both groups -conditional independence condition- and, because we were able to match each recipient district with at least one non-recipient district -common support condition-.

5. Results

5.1.   *Average impact: Diff-in-Diff*

Our identification strategy for impact of the mining revenue on outcomes at district level in Peru was based on data of 1839 Peruvian districts, of which 1362 naturally-endowed districts –or its close neighbors- were the treatment group, the remaining 477 non-mining districts were the control group. In our basic model, the treatment group is receiving a non-negligible amount[16] of mining transfers between 2007 and 2011 as a percentage of total revenue of the district. The evaluated outcomes were our estimations of poverty headcount rates (FGT0) and consumption inequality (Gini coefficient) at the district level for two different waves of poverty maps in 2007 (baseline) and 2011.

Inference of the average effect of the treatment was performed trough a diff-in-diff approach, under the assumption that the difference in the average gain over time of each group is an unbiased estimation of the average impact of the treatment on the selected outcomes.

Since belonging to the same Province or Region of the producer district is sufficient condition for being exposed to treatment, we define and control by an indicative variable for regions and provinces. Additionally, we take into consideration that transfers to all districts are not uniform, and depend, to some extent, on population size and unmet basic needs of each district. The index distribution of mining canon at the district level -obtained through a mathematical algorithm by the Central Government authorities- summarizes this information and is used as an additional control variable.

The results presented in Table 1 show our diff-in-diff estimate of impact with and without controls for the period 2007-2011. We estimate that, on average, transfer-receiving districts reduced poverty rates 10.6 percentage point more than non-receiving ones, an average of 2.65 points more per year. As for consumption inequality, we estimate that the Gini coefficient in treatment districts decrease 5.2 percentage points more than in control group –an average of 1.3 points per year more-. Both estimations are robust to different set of controls.

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[16] To operationalize this notion, we set the threshold for the treatment group in all the districts receiving 1% or more of their total revenue in the form of mining generated fiscal transfers. In our sample, the typical district in the treatment group received 32.3% of their fiscal revenue from mining transfers, with a standard deviation of +/- 23 percentage points, a maximum of 94.6% and a minimum of 1.03%.

Table 1

Diff-in-diff estimation of impact of mining transfers
on poverty rates and consumption inequality. District level, Peru 2007-2011

	Headcount poverty ratio	GINI index
No controls	-0.110***	-0.054***
	(0.017)	(0.004)
Regional and province controls	-0.105***	-0.052***
	(0.011)	(0.004)
Regional and distribution index controls	-0.106***	-0.052***
	(0.012)	(0.004)

Standard errors are presented in parentheses.
*** significant at 1 percent.

Table 2 shows that proportionally to the observed changes in the selected outcomes, our estimates of average impact were important in magnitude. Our estimate of average impact of mining revenues on poverty rates is equivalent to 56% of the observed change in poverty in the treated districts[17]. In the case of the impact ever Gini coefficient, estimated average impact is more than proportional to the observed change in the variable (138%), which was due to the fact that inequality levels in the control districts actually went up between 2007 and 2011.

Table 2

Estimates of average impact of mining transfers
and observed changes in outcomes. District level, Peru 2007-2011

	Observed				Estimated Impact 2011-2007	
	Control		Treatment		2011 - 2007	
	2007	2011	2007	2011		PP	%
Headcount poverty ratio	0.508	0.428	0.607	0.418	-0.19	-0.106	56
GINI index	0.288	0.304	0.288	0.250	-0.04	-0.052	138

The relatively better performance observed by mining districts could be related to the fact reported by Arreaza and Reuter (2012), who mentioned that those districts who receive *Canon Minero* had a higher level of public spending and public investments compared to non-mining districts. However, our results

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[17] It is important to point out that 2007-2011 was a period of rapid growth for Peru and the national poverty headcount rate dropped 15 percentage points (INEI, 2012)

differ greatly from this study since we consider different set of outcomes and data sources, and thus we are able to find a significant impact on outcomes.

Our results are more in line with Loayza *et al* (2012), who found evidence that mining producing districts have better average living standards than otherwise similar districts, including larger household consumption, lower poverty rate, and higher literacy; and those in Aragón and Rud (2013), who found positive effects of the mine's demand for local inputs on real income. However, differently from those studies, beside the difference in the two-points-in-time setting and the empirical strategy, we identify that the positive impacts over both, poverty and inequality, are at least partially associated with fiscal mining transfers in place.

5.2. *Quintile Diff-in-Diff Analysis*

We also use quintile difference-in-differences (QDID) model in order to identify heterogeneous responses to the canon on the entire marginal distribution of poverty and inequality. For this purpose we use the 2007 and 2011 distributions (quintile from 0.1 to 0.9) of these outcomes in the control districts to estimate a counterfactual distribution of outcomes in the treatment districts that would have existed in 2011 in the absence of the canon. The findings in this paper suggest that overall there is evidence of a heterogeneous response to the mining revenues.

The results of the Quintile Diff-in-Diff Analysis are presented in Table 3. We estimate that, on average, districts with lower poverty rates benefited more from the abundant-mining setting than districts with higher poverty rates. The estimated impact on districts of the first quintile of the distribution of FGT0 (-0.117) is almost 3.9 times higher than the estimated impact for the ninth quintile of the distribution of FGT0 (0.03). A somehow inverse relationship was found for the case of inequality levels, where the heterogeneous response of districts was characterized by stronger response to treatment of those districts with initial higher inequality levels. In the case of inequality, the estimated response of districts in the ninth decile of the distribution of Gini coefficient was almost 3.6 times stronger than the estimated impacts in the districts of the first quintile. See Figure 3 for an illustration of the heterogeneous estimated response to treatment by quintiles.

Table 3

Quintile Diff-in-Diff estimation of impact of mining transfers over poverty rates and consumption inequality. District level controls. Peru 2007-2011

	Headcount poverty ratio 1/	GINI index 1/
Quantile 0.1	-0.117***	-0.015***
	(0.016)	(0.001)
Quantile 0.2	-0.121***	-0.022***
	(0.017)	(0.001)
Quantile 0.3	-0.122***	-0.031***
	(0.014)	(0.001)
Quantile 0.4	-0.120***	-0.041***
	(0.011)	(0.001)
Quantile 0.5	-0.117***	-0.052***
	(0.010)	(0.002)
Quantile 0.6	-0.113***	-0.048***
	(0.012)	(0.002)
Quantile 0.7	-0.098***	-0.049***
	(0.013)	(0.003)
Quantile 0.8	-0.075***	-0.052***
	(0.012)	(0.003)
Quantile 0.9	-0.031**	-0.055***
	(0.013)	(0.005)

1/ with regional and distribution index as controls

Standard errors are presented in parentheses.

*** significant at 1%, ** significant at 5%

Figure 3

Estimated diff-in-diff coefficients by quintile of the outcome variable. Peru 2007-2011
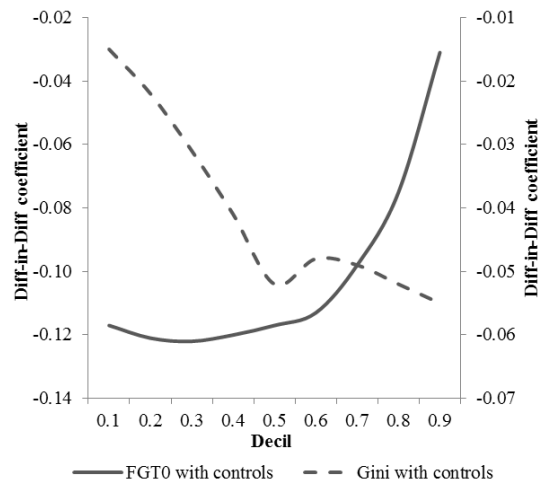
As seen in Table 4, for the 60% of districts with lower poverty levels, we find a more uniform impact. These districts benefited more from the mining boom between 2007 and 2011, and reduced the FGT0 by around 12 percentage points more than non-receiving districts (between 50% and 84% of their total observed reduction). From the seventh quintile to the ninth quintile, the FGT0 reduction due to the treatment was less important in magnitude and range from 17% to 50% of the total observed reduction.

Table 4
Quintile Diff-in-Diff estimation of impact of mining transfers over poverty rates
and consumption inequality. District level controls. Peru 2007-2011

| | Observed Headcount poverty ratio | | | | Estimated Impact 2011-2007 | | Observed GINI index | | | | Estimated Impact 2011-2007 | |
| | Control | | Treatment | | 2011 - 2007 | | | Control | | Treatment | | 2011 - 2007 | | |
	2007	2011	2007	2011		PP	%	2007	2011	2007	2011		PP	%
Quintile 0.1	0.193	0.138	0.263	0.123	-0.14	-0.117	86	0.250	0.217	0.232	0.186	-0.05	-0.015	33
Quintile 0.2	0.299	0.213	0.373	0.203	-0.17	-0.121	71	0.262	0.248	0.256	0.197	-0.06	-0.022	37
Quintile 0.3	0.374	0.336	0.479	0.282	-0.20	-0.122	62	0.274	0.262	0.269	0.207	-0.06	-0.031	50
Quintile 0.4	0.457	0.415	0.570	0.354	-0.22	-0.117	56	0.279	0.276	0.279	0.222	-0.06	-0.041	71
Quintile 0.5	0.524	0.452	0.654	0.421	-0.23	-0.113	50	0.285	0.288	0.289	0.242	-0.05	-0.052	110
Quintile 0.6	0.590	0.497	0.717	0.499	-0.22	-0.098	52	0.291	0.301	0.296	0.257	-0.04	-0.048	121
Quintile 0.7	0.657	0.547	0.776	0.553	-0.22	-0.075	44	0.300	0.331	0.307	0.266	-0.04	-0.049	120
Quintile 0.8	0.717	0.602	0.823	0.609	-0.21	-0.031	35	0.312	0.362	0.320	0.289	-0.03	-0.052	167
Quintile 0.9	0.798	0.671	0.870	0.691	-0.18	-0.031	17	0.335	0.430	0.337	0.324	-0.01	-0.055	421

These estimated heterogeneous results might be associated to the reduced ability of the poorest districts to get the full benefits of the additional investments made possible by mining resources from both public and private action. Higher poverty rates correlates with both, lower accumulated human capital and lower local government's capacity to effectively implement the projects funded by higher mining inflows.

In some sense, the same hypothesis could be applied to the heterogeneous response to treatment found by levels of inequality. Higher inequality could be associated with higher economic output and higher growth in per-capita incomes. As long as a Kuznets's curve-type relationship between growth and inequality holds at the local level in Peru, and in the extent that mining abundance allows more growth, at the initial levels of development we can expect stronger impacts in districts with higher inequality.

5.3. *On Dosage Effects*

Finally, we also tried to assess the potential heterogeneous responses of the districts by different levels of the treatment. In order to estimate the impact of marginal doses of mining revenues on the selected outcomes, as a proxy of the "intensity of abundance" of mining activities in each district, we constructed

artificial treatments groups sorting the mining districts by the relative importance of the mining transfers in their fiscal structure, using for that purpose official data on the ratio of mining transfers –canon plus royalties- over the total revenues at the district level.   We then divided the sample in 10% brackets -from 10% to 60%- and compared each artificial treatment group the original control group. We used the difference-in-difference approach on the selected outcomes –poverty and inequality- to estimate our measure of impact. Table 5 shows the results.

Table 5
Diff-in-Diff estimation of impact by level exposure to mining transfers.
District level controls. Peru 2007-2011

Outcome variable: Headcount poverty ratio

Mining revenues / Total revenues (%)	Baseline			Follow up			DID
	Control	Treated	Diff (BL)	Control	Treated	Diff (FU)	
>10%	0.167	0.462	0.296	0.082	0.290	0.208	-0.087***
>20%	0.167	0.505	0.338	0.082	0.323	0.241	-0.097***
>30%	0.472	0.846	0.374	0.387	0.655	0.268	-0.106***
>40%	0.167	0.551	0.384	0.082	0.345	0.264	-0.120***
>50%	0.294	0.635	0.341	0.208	0.421	0.212	-0.129***
>60%	0.477	0.789	0.312	0.392	0.568	0.176	-0.136***

Outcome variable: GINI index

Mining revenues / Total revenues (%)	Baseline			Follow up			DID
	Control	Treated	Diff (BL)	Control	Treated	Diff (FU)	
>10%	0.255	0.259	0.004	0.270	0.232	-0.038	-0.043***
>20%	0.345	0.349	0.004	0.360	0.319	-0.042	-0.046***
>30%	0.255	0.260	0.005	0.270	0.225	-0.045	-0.050***
>40%	0.324	0.343	0.019	0.339	0.304	-0.035	-0.054***
>50%	0.319	0.346	0.028	0.334	0.305	-0.029	-0.056***
>60%	0.261	0.300	0.039	0.277	0.262	-0.014	-0.053***

*** significant at 1%, ** significant at 5%

Our results confirm that poverty and inequality reduction at the district level in Peru is related also to the "intensity of abundance" of the mining resource. In fact, our *dosage* analysis suggests that mining abundance –proxied by the relative importance of mining revenues as a source of local fiscal income-might have had an incremental marginal impact on the selected outcomes during the commodity prices boom 2007-2011. The former fact suggests that more mining activity –implying more revenues, more private activity, etc.- meant on average stronger reduction in poverty rates and inequality levels vis-à-vis those non mining districts. Figure 4 presents an illustration of this result.

Figure 4

Estimated diff-in-diff coefficients of impact over selected outcomes.
Sorted by level of exposure to mining transfers. District level. Peru 2007-2011
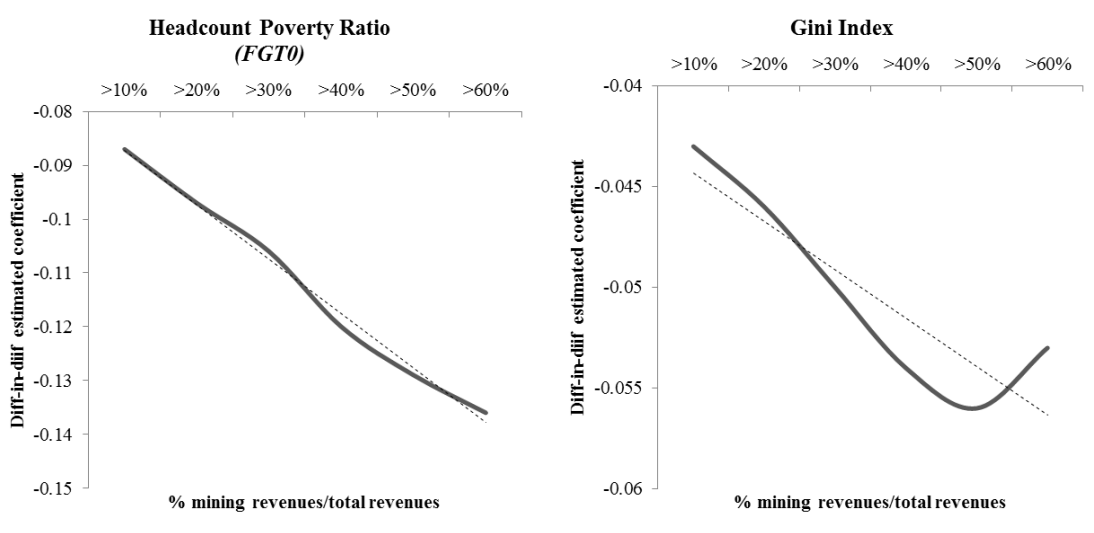
6. Final Remarks

First, this paper finds that the abundance of natural resources –proxy by fiscal mining transfers– has been not a curse, but beneficial for the receiving districts in Peru between 2007-2011. It is possible to make this assertion thanks to the particularities of the Peruvian case, whose legal framework creates systematic differences between mining districts and non-mining districts, allowing proper strategies for identification of impacts at the district level.

Second, ceteris paribus, mining activities allowed mining districts to cut poverty and inequality rates faster than non-mining districts. Given the magnitude and the robustness of the estimated impact (10.6 percentage points more on average for poverty and 5.2 percentage points for inequality), this effect cannot be easily dismissed[18].

Our results point at heterogeneity in the response to the treatment, with lower-poverty, higher-inequality districts showing, on average, stronger impacts. We also find that "intensity" of the treatment matters, with a trend suggesting that more mining-abundant districts did, on average, better than less mining-abundant districts in improving the outcomes of interest.

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[18] It is of importance to highlight that while our estimation uses fiscal data at the district level to separate mining districts from non-mining ones, the average impact effects estimations are not to be interpreted as the solely impact of mining revenues over the selected outcomes, but rather as the confluence of various factors like upward and downward linkages of the mining operations with the local economy, migration trends, etc.

The results of this research are suggestive, since it is commonly thought that in Peru, districts in general, and canon-recipient districts in particular, suffer from chronic administrative deficiencies that impede advancement on socioeconomic outcomes despite being recipients of abundant resources. While the kind of administrative weaknesses cited might be true, it is also true that regardless execution capacity, canon-recipient districts saw the <u>absolute level</u> of public expenditure/investments exponentially increased during the cited period.

More importantly, the findings on this paper cannot be interpreted as the sole effect of increasing fiscal revenues and expenditures at the local level, but rather as a confluence of multiple additional factors, including more private economic activity from the forward and backward productive linkages of the mining investments, changes in internal migration trends, among others. However, to pin the specifics of the potential channels of transmission of mining on welfare outcomes is beyond the scope of this study and certainly a fertile field for further research[19].

The results here presented offer insights on the nature of the recent local development dynamics in Peru. To the light of these results, the broader policy debate ahead on the role of natural resources exploitation in local development include policy issues like the optimal amount of mining transfers to districts; the analysis of progressivity of the current mining revenues distribution rules, and; the creation of across-the-board compensatory mechanisms for districts not "blessed" by geology.

References

Aragón, F. and Rud J.P. (2013). "*Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine*". American Economic Journal: Economic Policy 2013, 5(2): 1–25.

Arreaza, A. and Reuter, A. (2012). "*Can a Mining Windfall Improve Welfare? Evidence from Peru with municipal level data*". Corporación Andina de Fomento Working Papers. No. 2012/04.

Auty, R. M. (2000). "*How Natural Resources Affect Economic Development*". Development Policy Review, 18: 347–364.

Besfamille, M., Grossman, N., Manzano, O. and Sanguinetti, P. (2012). "*Public expenditure smoothing at the sub-national level: Evidence from Argentina*", mimeo IADB, Washington.

Brunnschweiler, C. N. & Bulte, E. H. (2008). "*Linking Natural Resources to Slow Growth and More Conflict*". Science 320 (5876): 616–617.

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[19] Further exploring the anatomy of transmission channels of how mining revenues impact the selected outcomes will be beneficial to proper asses both, the sustainability of the results, and the role played by interaction effects between districts and/or third party effects like the private sector.

Cavalcanti, T., Mohaddes, K. & Raissi, M. (2011). *"Does Oil Abundance Harm Growth?"* Applied Economics Letters.

Caselli, F. y Michaels, G. (2011). "*Do oil windfalls improve living standards? Evidence from Brazil"*. (NBER Working Paper N°15550). Cambridge: National Bureau of Economic Research.

Del Valle, M (2013). *"Ingresos fiscales provenientes de la explotación de recursos mineros e hidrocarburos en Perú"*. IADB Mimeo.

Elbers C., J. Lanjouw and P. Lanjouw (2003). *"Micro-level estimation of poverty and inequality"*. Econometrica, Vol. 71, No. 1 pp: 355-64.

Gelemur, A. and Pochat, L. (2011). *"Recursos naturales. ¿Bendición o maldición?: El efecto de las regalías petroleras en las provincias argentinas"*. Universidad Torcuato Di Tella, Buenos Aires, Argentina. Mimeo.

Gylfason, T. (2000). *"Resources, Agriculture, and Economic Growth. Economies in Transition"*. KYKLOS, Vol. 53, Fasc. 4: 545–580.

Gylfason, T. (2001). *"Natural Resources, Education, and Economic Development"*. European Economic Review 45: 847-859.

Gylfason, T. (2001). *"Nature, Power and Growth"*. Scottish Journal of Political Economy, Vol. 48, No. 5: 558-588.

Heinrich, C., Maffioli, A. and Vázquez, G. (2010). *"A Primer for Applying Propensity-Score Matching"*. Inter-American Development Bank Technical Notes. No. IDB-TN-161.

Imbens, G. and Wooldridge, J. (2009). *"Recent Developments in the Econometrics of Program Evaluation"*. Journal of Economic Literature 2009, 47:1, 5–86.

INEI (2009). *"Mapa de Pobreza Provincial y Distrital 2007"*, Lima, Perú.

INEI (2012). *"Informe Técnico. Evolución de la pobreza 2007-2011"*, Lima, Perú.

Kronenberg, T. (2004). *"The Curse of Natural Resources in the Transition Economies"*. Economics of Transition. Vol. 12, No. 3: 399-426.

Leuven E.and Sianesi. B. (2003). *"PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing and covariate imbalance testing"*. http://ideas.repec.org/c/boc/bocode/s432001.html.. Version 4.0.6.

Litschig, S. (2008). *"Financing Local Development: Quasi-Experimental Evidence from Municipalities in Brazil, 1980-1991"*. Economics Working Papers. 1142. Department of Economics and Business, Universitat Pompeu Fabra. Revised Oct 2010.

Loayza, N., Rigolini, J. and Calvo-Gonzalez, O. (2011). *"More than You Can Handle: Decentralization and Spending Ability of Peruvian Municipalities"*. World Bank Policy Research Working Paper Series.

Manzano, O. and Rigobón, R. (2001). *"Resource curse or debts overhang?"* NBER Working Paper N° 8390. Cambridge: National Bureau of Economic Research.

Mehlum, H., Moene, K. and Torvik, R. (2006). *"Institutions and the Resource Curse"*. The Economic Journal, 116: 1–20.

Papyrakis, E., and Gerlagh, R. (2004). *"The Resource Curse Hypothesis and its Transmission Channels"*. Journal of Comparative Economics, 32: 181-193.

Rodriguez, F. and Sachs, J. (1999). *"Why Do Resource-Abundant Economies Grow More Slowly?"* Journal of Economic Growth, 4: 277–303.

Rosenbaum, P., and D. Rubin. (1983). *"The Central Role of the Propensity Score in Observational Studies for Causal Effects"*. Biometrika 70(1): 41-55.

Ross, M. (1999). *"The Political Economy of the Resource Curse"*. World Politics 51: 297-322.

Sachs, J., and Warner, A. (1995). *"Natural Resources Abundance and Economic Growth"*. National Bureau of Economic Research Working Papers Series. No. 5398.

Sachs, J., and Warner, A. (2001). *"Natural Resources and Economic Development: The curse of natural resources"*. European Economic Review 45: 827-838.

van Wijnbergen, S. (1984). *"The `Dutch Disease': A Disease after All?"* The Economic Journal, Vol. 94, No. 373 (Mar., 1984), pp. 41-55.

Vega, J. (2008). *"Análisis del Proceso de Descentralización Fiscal en el Perú"*, Pontificia Universidad Católica del Perú, Departamento de Economía, Documento de Trabajo Nº 266.

Villa, J.M. (2011). *"DIFF: Stata Module to Perform Differences in Differences Estimation"*. Statistical Software Components. Boston College. Department of Economics.

Zambrano O. (2008). "*Corruption in natural-resource abundant countries: Some new evidence"*. Revista Nueva Economía. Academia Nacional de Ciencias Económicas de Venezuela, Caracas, Venezuela. May.

Annex I

Producing poverty maps for Peru 2011-2012

As mentioned, the identification strategy of this study relies heavily on the constructed set of estimations of a series of outcomes at the district level in Peru. For this study we replicated the methodology of poverty maps to produce two different waves of socioeconomic indicators at the lowest territorial level possible. We applied the Poverty Mapping Software developed by the World Bank (POVMAP) using two sources of information: the ENAHO survey and the structured micro data of the last National Census conducted in 2007.

This methodology, computationally demanding, allowed us to estimate poverty incidence, extreme poverty incidence and inequality of the consumption distribution (Gini coefficient) for 2007 and 2012. We followed the methodological procedure described by Elbers *et al* (2003).

This procedure consists of three stages. In the first stage, the census and survey data are examined for compatibility. Only the variables with same definition and statistically similar are allowed to be used in the next stage. Given we used the same census (2007), these variables were those whose census mean lies within the confidence interval of the same variable in the 2011 survey data, with the interval being estimated taking into account the information of the sample design. The result of this test implies that the selected variables are similar on the date of the surveys and, consequently, it is possible to estimate indicators for this date.

In the second stage or the modeling stage, a series of regressions –based on the 2011 ENAHO household data for 2011 poverty maps– was run (with generalized least squares) to model the consumption and decompose the random unexplained components, with the explanatory variables being those common to both the survey and the census. Once a believable consumption estimation model is obtained, in the third stage or simulation stage, the model parameters are used to perform repeated drawings (100 times) on different random components to bootstrap the consumption of each census households. Then the mean and standard deviation of outcomes are estimated and aggregated at the district level. The three stages were made for each representative geographical area defined by the survey sample design (25 departments) in order to obtain accurate estimates.

The lineal expression of the constructed model is $Ln_{sh} = X'_{sh} + u_{sh}$, where Ln_{sh} is the logarithm of the per capita consumption of the household h in the cluster s (areas of the districts), X'_{sh} is a matrix of the

observed characteristic of this household and u_{sh} is the error term with a distribution $F(0, \Sigma)$. In order to reduce the fixed effects and the presence of heteroscedasticity u_{sh} was decomposed into two independent components non-correlated with X'_{sh}: the component, common to all household in each cluster, and the residual component e_{sh} related to the households' characteristics. The first one is reduced adding variables constructed at the cluster level on the right hand side of the equation, and the second one by detecting variables that generate heteroscedasticity.

Annex II

Robustness Check: Propensity Score Matching

For a matter of robustness, we also performed another non-experimental evaluation approach to compare how outcomes differ for mining districts relative to observationally similar non-mining districts. We applied a propensity-score matching approach using a set of cofound variables at the district level to estimate the conditional probability of being in the treatment/control group. In particular, we estimated the propensity score controlling by geographical (surface, altitude, natural region), demographic (population density), initial living conditions in 2005 (literacy rate, school enrollment, life expectancy and per capita income), and local public sector relative size (number of public employees per capita, and per capita total fiscal revenue). The outcome variable was set to be the change in levels of our two preferred welfare indicators at the district level, poverty rates and Gini coefficient at the district level. We were able to fulfill common support assumption for our estimates. Table 6 shows our basic participation model.

Table 6
Basic Participation Model for the Propensity Score Matching
District level controls. Peru 2007-2011

Probit regression

	Coef	SE	P-value
Average altitude	0.001	0.0001	0.000
Population density	0.000	0.0000	0.000
Share of public employment	-6.008	1.3228	0.000
Coast region	2.776	0.2596	0.000
Mountain region	3.233	0.2582	0.260
Fiscal revenue (per capita)	0.000	0.0000	0.000
Life expectancy (2005)	0.074	0.0178	0.589
Literacy (2005)	0.004	0.0071	0.040
School attendance rate (2005)	-0.011	0.0055	0.000
Percapita income (2005)	0.005	0.0008	0.000
Constant	-8.593	1.2574	0.000
LR chi2(10)	1161		
Prob > chi2	0.00		
Pseudo R2	0.57		
Log likelihood	-444.6		

For additional robustness in the interpretation of the results, we evaluated the estimated treatment effect under alternative matching algorithms or by altering the parameters of a given algorithm. Our results do not depend crucially on the particular methodology chosen and confirm the findings of the previous

section. Using the PSM approach we find evidence of impact of mining transfers over poverty rates and inequality indicators. Coefficients of average treatment effect on the treated (ATT) and average treatment effect (ATE) were estimated using different matching algorithms. The results are shown in Table 7.

Table 7
Propensity Score matching estimation of impact of mining transfers
over poverty rates and consumption inequality
District level controls. Peru 2007-2011

Outcome Headcount poverty ratio	Nearest neighbor (1)	Nearest neighbor (5)	Kernel matching (epanechnikov)	Kernel matching (normal)	Radius matching (0.05)	Local linear regression
ATT	-0.0842**	-0.0968**	-0.0894***	-0.0764***	-0.0886***	-0.1072***
(T or Z stat)	(-3.27)	(-3.51)	(-5.35)	(-5.54)	(-5.26)	(-4.56)
ATE	-0.0671*	-0.0806**	-0.0749***	-0.0637***	-0.0748***	-0.0830***
(T or Z stat)	(-2.77)	(-3.37)	(-4.76)	(-4.45)	(-4.88)	(-3.87)
Common support	1780	1780	1789	1810	1780	1810
GINI index	Nearest neighbor	Nearest neighbor	Kernel matching (epanechnikov)	Kernel matching (normal)	Radius matching (0.05)	Local linear regression
ATT	-0.1073***	-0.1158***	-0.1107***	-0.1199***	-0.1118***	-0.1087***
(T or Z stat)	(-4.17)	(-4.27)	(-6.54)	(-9.81)	(-5.72)	(-3.89)
ATE	-0.0965***	-0.1006***	-0.0971***	-0.1027***	-0.0977***	-0.0955***
(T or Z stat)	(-4.89)	(-4.86)	(-6.52)	(-10.02)	(-6.46)	(-4.92)
Common support	1663	1663	1680	1670	1663	1663
Caliper	0.05	0.05	-	-	0.05	-
Kernel denisity function	-	-	epanechnikov	normal	-	tricube
Bootstrap SE	No	No	Yes	Yes	Yes	Yes
Abadie & imbens SE	Yes	Yes	No	No	No	No

*** significant at 1%, ** significant at 5%, * significant at 10%

As shown in Table 7, we were able to estimate significant impacts of the mining revenues over the selected welfare outcomes. The point-estimate for the impact over the selected outcomes is a little lower/higher than previous section's estimations, which might be due to the use of additional controls in the participation model and more restrictive matching conditions. However, in general, trough the PSM approach we estimated average treatment effects on the treated (ATT) and average treatment effects (ATE), that coincide in order of magnitude, sign and significance with those obtained through the diff-in-diff approach.