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Mining and Human Capital Accumulation: the Role of the Return to Education

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Abstract: The literature has long tried to explain the casual relationship between natural resources booms and human capital accumulation but yet with no definitive answer. Usually the literature finds that booms abates the process of human capital accumulation by increasing the cost of opportunity of studying. We want to further contribute to this discussion by studying the impact of the mineral mining boom in Peru on the interruption of post-secondary studies during the period 2004-2016. To do so, we rely on a differences-in-difference strategy. Our results show that the Peruvian mining boom had a positive impact on the probability of interruption of post-secondary studies. Furthermore, the probability of staying idle of young individuals increased. In contrast with previous studies, we find that our results are driven mainly by a decrease in the return to higher education relative to high-school education. Other mechanisms that may be playing a minor role is the health status of young individuals -which deteriorates with the mining boom-, and the labor reallocation that occurs within households.

JEL Classification Codes: D13, I23, J46, O13.

1 Introduction

The literature has long tried to explain the casual relationship between natural resources boom and human capital accumulation but yet with no definitive answer. Usually, studies find that resources booms inhibit the process of human capital accumulation by increasing the cost of opportunity of studying: individuals prefer to enter the labor market and make use of the higher wages induced by the boom (Morissette, Chan, Lu, 2015; Atkin, 2016; Angrist and Kluger, 2008; Black, McKinnish, and Sanders, 2005; Cascio and Narayan, 2015; Emery, Ferrer, and Green, 2012; Charles, Hurst and Notowidigdo, 2015). However, this substitution effect can be offset by an income effect: parents earning more may send their children to school (Lovenheim, 2011). Furthermore, other channels can be playing a role too. In particular, the whole structure of the returns to education can be affected by the boom. For instance, completing a certain academic level can be more than rewarded after the boom (Heath and Mobarak, 2015; Atkin, 2016).

The main contribution of this study is to show that the cost of opportunity channel is not the main channel by which natural resources boom affect the process of human capital accumulation (i.e. the completion of post-secondary studies), at least for our sample. We show that mining production reduces the return to post-secondary education, thereby, inducing potential students to stop their studies. Moreover, we show that other channels, usually neglected by the literature, such as the deterioration of health and the labor reallocation within households, can also affect the completion of post-secondary studies, but seem to be playing a minor role.

Our empirical strategy relies on three facts. First, mineral prices are exogenous to college decisions because the Peruvian economy is a price-taker of international prices of the most important commodities it produces. Furthermore, during the 2000s decade, Peru experienced some drastic changes: mineral prices quintupled, hence the total value of mineral production increased dramatically (Aguero, Maldonado, and Ñopo, 2016). Second, each district is specialized in the production of certain minerals according to their natural reserves. Thus, we exploit the cross-section variation generated by the different types of minerals produced. Third, mining firms choose where to produce depending on the availability of natural reserves and not focusing whether they are going to find skilled labor or not. In addition, to start production, mining firms have to undergo through a very large process of exploration and preparation.[1] All in all, we use the within-district variation on the value of production, which means that identification comes from year-to-year variation in the production within a district.

This paper makes several contributions to the literature. First, we focus on higher education, topic that, relative to high-school, is understudied by the literature of natural resources. To the best of our knowledge, this paper would be one of the first in studying the link between the boom of natural resources and higher education interruption. Only Morissette, Chan, and Lu (2015), Toews and Libman (2017), and Ahlerup, Baskaran, and Bigsten (2016) explore this topic to some extent. Second, we show that mining booms can affect the return to education, thereby, creating incentives for individuals to interrupt their studies. Some papers find that changes in the return to education caused by specific phenomenons -such as fracking- are associated with changes in enrollment and educational attainment. For instance, Cascio and Nayaran (2015) find that local labor demand shocks from fracking have reduced the return to high school completion among men, increasing high-school dropout rates of male teens. Third, we provide evidence of other mechanisms that usually the literature has neglected, such as health and labor reallocation within household.

We find that mining production decreases the probability that an individual continues with her post-secondary studies. Given that from 2003 to 2015, mining per capita increased, in average, by US$ 20 thousand in real terms, our estimations suggest that the probability of continuing with post-secondary studies decreased by more than 1 percentage point in mining areas relative to non-mining areas. This effect is relatively small but robust to several specifications. Furthermore, we show that these individuals are interrupting their studies to stay idle at home: they are not getting employed, hence, the cost of opportunity does not seem to be a relevant channel in the context of our sample. Rather, we find that the main driver is the return to education, since the return to post-secondary education decreases relatively to the return to higher education. We validate this hypothesis by

[1] Usually, mining explorations takes more than 10 years to be completed.

carrying out an exercise of falsification. We show that potential high-school students are not interrupting their studies. Finally, we find that other channels may be playing a minor role too, such as the health status and the employment reallocation withing households.

The remaining of this paper is divided in the following way. First, Section 2 briefly explains the institutional and economic framework of the country we are studying: Peru. Section 3 describes the theoretical background. Section 4 shows the empirical strategy exploited and the data used. Section 5 explains our main results. Section 6 discusses the mechanisms that may be behind our results. Section 7 discusses whether endogenous migration is driving our mains results and other robustness tests. Finally, Section 8 concludes.

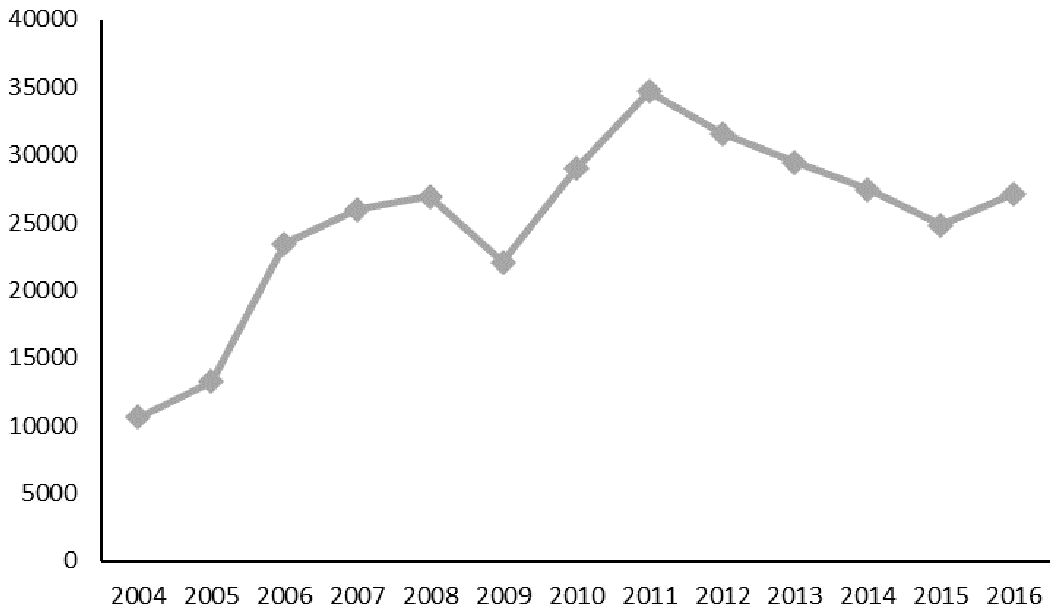
2 Institutional Framework

2.1 Mining Regulations

Peru has always been a mining country. In the recent history, mining regulations has shaped the development of this activity. During the 90s, several laws that fostered foreign direct investments on mining were passed. For instance, property rights limitations to foreign investors were removed. Even land expropriations were allowed for those cases in which the land owner did not want to sell his property. As a result, in 2001 mining investments were of US$ 1.595 billion, whereas in 1996 they were of US$ 387 million (Maldonado 2014).

To further grasp the magnitude of the boom, in Figure 1 we plot the mining production (in US$ million) over time. It can be seen that mining production rose from around US$ 10'000 million to approximately US$ 35'000 million in 2011 and US$ 27'000 million in 2016. In other words, mining production was tripled in a period of just twelve years.

Figure 1: Mining Production (Million US$)

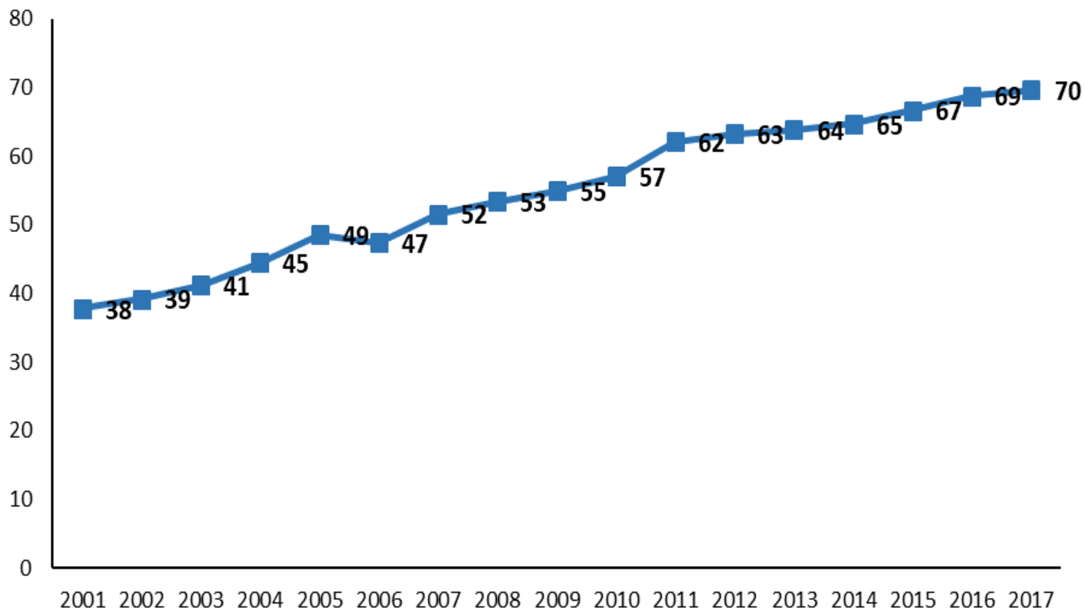


Source: Ministry of Energy and Mines, Ministry of Economy

2.2 Higher Education in Peru

In January 1995, the Government passed a new law that authorized every natural or legal person to promote, conduct and manage any private initiative regarding educational institutions. Before this law, only legal persons could establish private universities, providing that she was going to manage the university as a non-profit organization. As a result of these changes, legal entry barriers were decreased significantly. As a matter of fact, from 1997 to 2007, 35 universities were created, and, from 2008 to 2012, 42 new universities were established. This expansion of the supply substantially increased the number of enrolled students and applicants: enrollment increased from 38% in 2001 to 70% in 2017. However, as Yamada, Lavado and Martinez (2015) show, this process was accompanied with a wear down of institutions' quality. We expect that, in spite of this nationally-wide positive trend, post-secondary enrollment in mining areas has grown more slowly relatively to non-mining areas.

Figure 2: Enrollment in Post-Secondary, 2001-2017



Source: Ministry of Education

3 Theoretical Background

Educational choices can be thought in a multi-period model where individuals have to choose among distinct education levels, for instance, primary, high-school and post-secondary. This choice is irreversible: they can either work or obtain an additional level of education. These individuals derive utility from studying by increasing their earnings in the labor market: if they earn a higher education level, they will receive a larger wage. However, to attain a higher education level they have to stop working, hence losing any utility gain coming from present income. They also have to incur in other psychic and physical costs. An impatient student will choose to work instead of studying (Atkin, 2016). All in all, according to the human capital theory (Becker, 1994), rational agents will dropout from attaining a certain educational degree, for instance a post-secondary degree, if the net present discounted value (PDV) of dropout exceeds that of completion.

Up to now, we have assumed that individuals are not credit-constrained and that studying is not a consumption good. In the context of credit constrains, the household's income may affect the individual's choice. Following Lovenheim (2011), consider a credit-constrained student. For this student, it would be optimal to earn a post-secondary degree, however, her family lacks access to credit. In this scenario, increasing income or wealth may affect her final choice on whether to study or not. Similarly, when education is a consumption good (either for parents or students), income and wealth can affect college decisions: if her family is wealthier, they are going to consume more of all normal goods, including education (Lovenheim, 2011).

In this way, natural resources shocks have multiple pathways to affect enrollment decisions. If natural resources shocks increase the cost of opportunity of studying by fostering employment opportunities for the young and uneducated, then enrollment will decrease. In addition, natural resources shocks may also affect production factors' return. For instance, if certain shock decreases the return to post-secondary education, then individuals in the margin will choose to dropout (see Cascio and Nayaran, 2015). Furthermore, natural resources shocks can also affect income within households. If households are, in average, becoming poorer -thanks to the externalities inherent to the exploitation of natural resources (see Aragon and Rud, 2013; Loayza and Rigolini, 2016), and education is a normal good, then families in the margin will withdraw their children (see Lovenheim, 2011; Dahl and Lochner, 2012; Bulman et al., 2016). The final result is ambiguous and depends on the magnitude and direction of each effect (Atkin, 2016). Usually, the literature has found that the substitution effect (i.e. the cost of opportunnity channel) is larger, at least for high-school enrollment (see, for instance, Black, et al., 2005; Emery, et al., 2012; Foote and Grosz, 2017).

4 Empirical Strategy

4.1 Identification

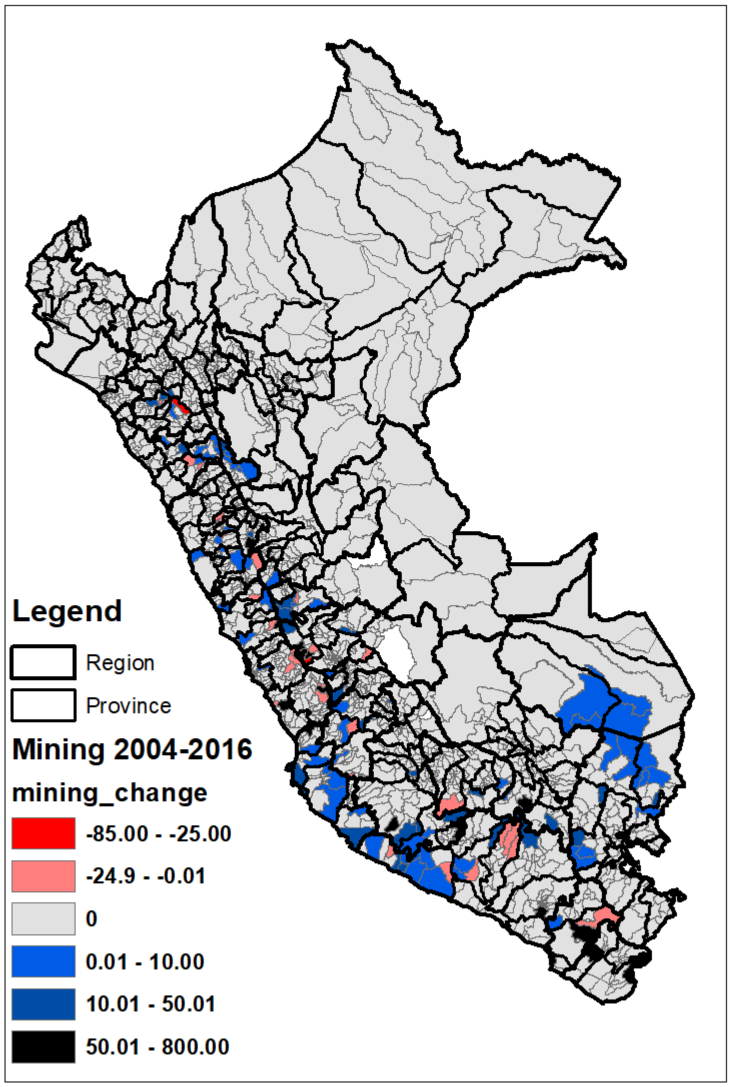
The main objective of this study is to identify the causal effect of the mineral resource boom (or bust) on the probability that a soon-to-be or current student continues with her studies given that she approved the previous academic year. In order to identify this causal effect, we rely on the cross-section variation of mineral production and mineral resources across districts and on the time-series variation of mineral production and prices. Figure 2 exemplifies the variation we are using to identify our parameter of interest. We are comparing mining areas (colored with black, blue or red) with non-mining areas (grey colored). To justify the exogeneity of these variations we will argue the following points.

First, mineral prices are exogenous to college decisions because the Peruvian economy is a price-taker of international prices of the most important commodities. It is well known that the last cycle of changes of international prices were driven, first, by the rapid industrialization of the Chinese economy and, second, by the global meltdown caused by the U.S. housing bubble (Maldonado, 2014). Second, each district is specialized in the production of a certain set of minerals depending on the natural reserves they have. Thus, we exploit the cross-section variation generated by the different types of minerals produced.

Third, mining firms choose where to produce depending on the availability of natural reserves and not focusing on whether they are going to find skilled labor or not. In addition, to start production, a mining firm have to undergo through a very large process of exploration and preparation. Fourth, it is possible that some local governments may attract mining companies by investing in such a way that is correlated with individuals' higher education decisions. However, we think this is not plausible since all mining permits are granted by the Ministry of Energy and Mines, the Ministry of Environment, and the Ministry of Culture (Aguero, Maldonado, Ñopo, 2016).

By including district fixed effects, we control for any other unobserved variable at the district level simultaneously correlated with mining production and college decisions (including the concern raised in the last paragraph). In other words, as in Aguero, Maldonado, Ñopo (2016), we use the within-district variation on the value of production, which means that identification comes from year-to-year variation in the production within a district. As part of our specification, time-fixed effects will help us control for any other unobserved factor correlated with mining production and college decisions across time. All in all, by including year and district fixed effects, our approach is equivalent to exploiting a differences-in-difference strategy. We augment this approach by including province-specific linear trends and region-year fixed effects to further control for any unobservable varying linearly at the province level or at the region-year level.

Figure 2: Change in Mining Production per Cápita (2004-2016) (Thousands Real US$)



Source: Ministry of Energy and Mines, Ministry of Economy

4.2 Empirical model

Our basic specification is:

$$\begin{aligned} Y_{i,j,t} &= \beta_1 Q_{j,t-1} + X'_{i,j,t}\delta_1 + \alpha_j + \alpha_t + [\alpha_{province} \times Trend_t] \\ &+ [\alpha_{region} \times \alpha_t] + \varepsilon_{i,j,t} \end{aligned} \quad (1)$$

where $Y_{i,j,t}$ is the dependent variable (i.e. a dummy that takes the value of one whether the individual i, located at district j, on year t chooses to enroll to higher education given that she already finished secondary education or the previous year of education; more on that later). Furthermore, α_j and α_t are district and time fixed effects; $Q_{j,t-1}$ is a measure of mining production per capita for district j in period $t-1$;[2] $X_{i,j,t}$ is a vector of individual and household controls. We divide this set in two subsets: i) covariates such as, maternal language, sex, whether the individual studied her previous year of education in a public institution, whether the individual live in a rural district, age, month dummies and mining canon per capita, ii) background or household covariates such as number of brothers, number of sisters, individual's birth order, whether the individual belongs to a family in which the first born child was a boy, whether the individual belongs to a family where the mother is the household's head, number of household members, education of the father and the mother, maternal language of the father and the mother, and age of the father and the mother.[3] In some specification we also include province-specific linear trends and region-year fixed effect, which are represented by $[\alpha_{province} \times Trend_t]$ and $[\alpha_{region} \times \alpha_t]$, respectively. Last but not least, all standard errors are clustered at the district level.

4.3 Data

We use several sources of data. We exploit a national representative household survey (ENAHO)[4] and combine it with data regarding mining production reported monthly by

[2] Note that we are using a lagged measure of mining production.

[3] In the tables below, we have tagged the first set of covariates with the name of "Controls". We have tagged the second set with the name of "H.H. Controls".

[4] This survey is stratified at the regional level and is carried out yearly by the National Institute of Statistics (INEI). It contains detailed information about living conditions at the household level (e.g. expen-

the Ministry of Energy and Mining at the product-per-firm level.[5] In order to match it with the household survey, we collapsed it at the district-product-year level. Then, we multiplied each figure by the international price corresponding to each product.[6] As a result, we obtain a database showing the value of mining production per year for each district.[7]

We also employ data from other sources such as figures for the mining windfall revenues collected by the Government. This data comes from the Ministry of Finance, which is the institution that compiles, computes and report this data at the district-year level.[8] The population at the district-year level come from the National Institute of Statistics.

4.4 Definition of Main Outcome and Final Sample

Using the national household, we construct a dummy that takes the value of 0 when the individual passed the previous academic year, including the last year of high-school, the first year of post-secondary education, the second year of post-secondary, and so on. Furthermore, this dummy takes the value of 1 when such an individual was enrolled at the time she was surveyed. This dummy is our main outcome of interest. Note that this dummy has a missing value when the individual does not satisfy these two conditions. Hence, our sample is composed of 47,304 observations (we only considered the household head's offspring). There are some advantages of defining our sample in this way. First, it allows us to identify with certainty the set of potential students (i.e. those that passed the previous academic year). Second, ENAHO's respondents report some characteristics of their last year school or institution. Thus, we can condition our regressions on such characteristics. Finally, individuals that migrate to study in a university far away from their home usually

ditures, access to public utilities, and household's construction materials, etc.) and socio-demographics and other characteristics at the individual level (e.g. sex, age, educational attainment, income, etc.), which are used to measure poverty and living standards. The sample size for each year is between 19,000 and 25,000 households.

[5] For this study, we converted these amounts to 2010 prices in U.S. thousand dollars per-capita.

[6] Data on international prices are obtained from the World Bank's web page.

[7] We only used the figures for gold, copper, tin, iron, lead, and silver, which are the main minerals produced in Peru.

[8] Mining Canon transfers are defined as the monetary transfers to local districts from the central government. These transfers are funded by the mining taxes.

live alone, or at least without their parents. Hence, the concern of endogenous sorting is lessened on this population (more on this in Section 7.1).

To control for a rich set of background variables, we further restrict our sample to those individuals currently living with both of their parents. This allows us to condition on their parents' characteristics, such as education, age, and race. By doing this, we can also study the labor outcomes of their parents: we can explore whether mining affected their parents' employment rates, wages, and so on. Usually the literature has ignored household dynamics when studying the impact of natural resources on variables such as enrollment. However, there is a strong literature showing unitary household behave differently than collective households (see a practical implication in Black, Devereux and Salvenes (2005) or a more theoretical build up in Cherchye, de Rock and Vermeulen (2007)). As a result of these cuts, the sample was reduced to 37,164 observations. After including all controls used in our main regression, we were left with 35,023 observations because of non-response.[9]

4.5 Descriptive Statistics

In Table 1 we describe the main characteristics of our sample. The variables are: the probability of continuing studying, of working on a paid job, and of staying idle, the household's total income and expenditures, the probability of reporting an acute disease and a chronic disease, each parents' years of education and age, the proportion of women, the proportion of quechua speakers, age, whether the individual lives in a rural district, whether the individual lives in a different district where she was born, whether the individual's household is poor and extremely poor, and mining production. For each variable, we compute the average and the standard deviation (in parenthesis). In (1) we show the average of these variables for the full sample. In (2), we exhibit the averages for mining districts in the period 2004-2010, whereas, in (3), we show the same average for the period 2010-2016.

[9] Our variable of interest (i.e. mining production) is uncorrelated with the probability of living in a one-parent household. To evaluate this issue we ran a regression similar as in equation (1) but without considering the set of controls and using as dependent variable a dummy that takes the value of zero if individual i is currently living with her both parents (N=37,164), and the value of one if she is living in other type of households (N=11,349). Results are robust to the inclusion of province-specific linear trends and region-year fixed effects. We also explored whether household's type (i.e. two or one parent) is linked with the probability of continuing with post-secondary studies an we found that it was not.

Finally, we calculate these averages for non-mining districts in column (4) and (5).

Table 1: Descriptive Statistics of Final Sample

Variables	Full Sample	Mining		Non-Mining	
		[2004-2010]	[2010-2016]	[2004-2010]	[2010-2016]
	(1)	(2)	(3)	(4)	(5)
A. Outcome and Mechanisms Variables					
Prob. of studying Higher Educ.	0.44	0.42	0.44	0.42	0.45
	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)
Prob. of working	0.45	0.44	0.42	0.47	0.45
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Prob. of staying idle	0.15	0.16	0.16	0.15	0.15
	(0.36)	(0.37)	(0.36)	(0.36)	(0.36)
Annual Income (thousand US$)	13.49	11.92	16.10	10.38	15.24
	(12.79)	(10.70)	(12.75)	(10.96)	(13.48)
Annual Expenditures (thousand US$)	11.01	9.05	11.96	8.66	12.43
	(7.40)	(5.39)	(6.8)	(6.04)	(7.80)
Acute Disease	0.52	0.50	0.56	0.50	53.0
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Chronic Disease	0.21	0.12	0.22	0.15	0.24
	(0.41)	(0.33)	(0.42)	(0.36)	(0.43)
B. Demographic Variables					
Fathers' Years of Education	11.21	10.53	10.86	11.00	11.38
	(4.30)	(4.33)	(4.15)	(4.39)	(4.24)
Mothers' Years of Education	9.49	8.62	9.24	9.13	9.72
	(4.95)	(4.42)	(4.97)	(4.99)	(4.92)
Fathers' Age	51.10	49.80	50.36	50.92	51.36
	(8.35)	(7.16)	(8.28)	(8.21)	(8.46)
Mothers' Age	47.20	45.99	46.69	46.93	47.53
	(7.40)	(7.16)	(7.26)	(7.30)	(7.42)
Women	0.49	0.50	0.50	0.47	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Quechua	0.08	0.04	0.05	0.08	0.09
	(0.27)	(0.21)	(0.22)	(0.27)	(0.28)
Age	20.29	19.83	20.13	20.03	20.31
	(3.58)	(3.22)	(3.40)	(3.49)	(3.66)
Rural	0.19	0.17	0.22	0.18	0.19
	(0.39)	(0.38)	(0.42)	(0.39)	(0.39)
Born in a different district	0.43	0.34	0.35	0.45	0.43
	(0.50)	(0.47)	(0.42)	(0.49)	(0.50)
Poverty	0.17	0.19	0.10	0.26	0.12
	(0.38)	(0.39)	(0.31)	(0.44)	(0.33)
Extreme Poverty	0.02	0.02	0.01	0.04	0.02
	(0.21)	(0.15)	(0.11)	(0.20)	(0.13)
C. Lagged Mining Production					
Production (in thousand US$ per person)	2.62	27.24	37.42	0.00	0.00
	(36.74)	(107.37)	(137.03)	(0.00)	(0.00)
Observations	35,955	1,103	1,854	13,507	21,985

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.

The first feature we observe is that in average the probability of continuing in higher education is a little bit larger for the non-mining areas. If we compute the difference between column (3) and (2) and subtract the difference between (5) and (4), the result is about one percentage point. This estimate is equivalent to a differences-in-difference estimation that roughly measures the impact of mining. Doing the same exercise for the probability of working, we find a result equal to zero. Mining-areas are a little bit richer than non-mining areas. However, computing the rough differences-in-difference estimate gives a result of -0.69 thousand US$, which suggests that mining areas are getting poorer. Moreover, it seems that the probability of reporting an acute disease is a little bit larger in mining areas, whereas the probability of reporting a chronic disease is a little bit smaller in non-mining areas. Nonetheless, computing the differences-in-difference estimation gives a result of +3.0 percentage points and +1.0 percentage points, respectively. Hence, it seems that individuals are getting sicker in mining areas.

Furthermore, parents are more educated and older in non-mining areas, in average. However, the rough differences-in-difference estimation gives a result of approximately zero for both variables, which suggests that selective sorting into and out from mining areas is not a concern, at least according to these variables. However, computing the differences-in-difference estimator for the prevalence of women and quechua-speakers results in a value of -2.0 percentage points for the prevalence of women, but 0.0 for the prevalence of quechua-speakers. This suggests that the net flow of male individuals into mining areas is larger than the net flow of female.

Moreover, individuals deciding whether to study or not are a little bit older in non-mining areas, although the difference between mining and non-mining areas across time periods is almost zero. It is interesting that mining areas started being less rural than non-mining areas, but by 2010-2016, this trend was reversed: mining areas were more rural than non-mining areas. It also important to note that the probability migration is larger in non-mining areas. In addition, computing the rough differences-in-difference estimation gives as a result a number of +3.0 percentage points. This raises some concerns regarding endogenous migration that we will further evaluate in Section 7. Finally, poverty seems to have decreased a lot faster in non-mining areas than in mining areas. The differences-in-difference estimation gives a result of +5.0 percentage points. All in all, mining and non-mining areas are different with respect to several variables. Nonetheless, these differences can be controlled when conditioning on district fixed effects, as long they remain constant across time. We will try to control for changes in these differences by conditioning on province-linear trends and region-year fixed effects.

5 The Impact of Mining Production: Main Results

Table 2 exhibits the results for equation (1) using three dependent variables. The dependent variable under Panel A is the probability of continuing with post-secondary studies as it was defined in Section 4.4. The dependent variable under Panel B is the probability of being employed on a paid job. Panel C is the probability of being idle, i.e. neither studying, neither working (given that the individual passed the previous year of education). Every specification includes district fixed effects and year fixed effects. Moreover, under column (1) we show our base specification including a small set of covariates, as it was described in section 4.2. Then, under column (2) we augment this specification with a set of background covariates. Under column (3) we include region-year fixed effects, and in column (4) we also include province-specific linear trends. Most of the tables in this paper have a similar format as the one presented for this table.

Panel A of Table 2 shows that the probability of continuing with post-secondary studies (i.e. the probability of not interrupting her studies) decreases with mining production per capita. Given that from 2003 to 2015, mining per capita increased, in average, by US$ 20 thousand in real terms, our estimated β_1 suggests that the probability of continuing with post-secondary studies decreased by more than 1 percentage point in mining areas relative to non-mining areas. From unreported coefficients, we know that the probability of continuing with post-secondary studies increased in about 6 percentage points during 2004-2016. Hence, in mining areas, the probability of continuing with post-secondary studies increased in 5 percentage points. This effect is relatively small but robust to several specifications. Our estimated β_1 remains almost unchanged when we include a set of background covariates, region-year fixed effects, and province-specific linear trends. Note that from now and onward our preferred specification will be the one under column (3) (i.e. with the inclusion of region-year fixed effects). The inclusion of region-year fixed effects *and* province-linear trends is costly in terms of degrees of freedom.

Table 2: The Effect of Mining Production

	With Covariates	With HH. Covariates	With Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)
Panel A: Probability of continuing post-secondary studies				
Lagged Production	-0.000584**	-0.000548**	-0.000543**	-0.000531*
	(0.000234)	(0.000246)	(0.000270)	(0.000302)
Mean of Dep. Var.	0.445	0.445	0.445	0.445
Adjusted R^2	0.143	0.144	0.144	0.144
Districts	1348	1348	1348	1348
Observations	35109	35023	35023	35023
Panel B: Probability of working on paid job				
Lagged Production	-0.000028	-0.000123	-0.000140	-0.000196
	(0.000165)	(0.000183)	(0.000203)	(0.000197)
Mean of Dep. Var.	0.451	0.451	0.451	0.451
Adjusted R^2	0.0755	0.101	0.103	0.104
Districts	1348	1348	1348	1348
Observations	35056	34970	34970	34970
Panel C: Probability of being idle				
Lagged Production	0.000472**	0.000427**	0.000411**	0.000386*
	(0.000205)	(0.000201)	(0.000187)	(0.000212)
Mean of Dep. Var.	0.151	0.151	0.151	0.151
Adjusted R^2	0.144	0.146	0.148	0.148
Districts	1348	1348	1348	1348
Observations	35088	35002	35002	35002
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
L. Trends				X

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Usually, the literature have shown that natural resources booms abates the process of human capital accumulation by increasing the cost of opportunity of studying (Morissette, Chan, Lu, 2015; Atkin, 2016; Angrist and Kluger, 2008; Black, McKinnish, and Sanders, 2005; Cascio and Narayan, 2015; Emery, Ferrer, and Green, 2012; Charles, Hurst and Notowidigdo, 2015). However, for our study, under Panel B we can observe that the probability of being employed changes in almost zero percentage points.[10] As a matter of fact, Panel C shows that the decrease in the probability of continuing with post-secondary studies is fully countervailed by an increase in the probability of staying idle.

6 Mechanisms

6.1 The Return to Education

According to the human capital theory (Becker, 1994), rational agents will dropout from attaining a certain educational degree, for instance a post-secondary degree, if the net present discounted value (PDV) of dropout exceeds that of completion. Traditionally, the net PDV of dropout is modeled as the PDV of lifetime earnings without the post-secondary degree, whereas the PDV of completion is the lifetime earnings with a post-secondary degree minus psychic costs and the opportunity cost. Hence, mining booms can induce someone to drop out by i) increasing the opportunity cost of remaining enrolled, and ii) by increasing expectations of a dropout's earnings (Cascio and Nayaran, 2015; Atkin, 2016). We have already showed, that the opportunity cost of remaining enrolled is unaffected by the mining boom, but we still need to test whether lifetime earnings are affected.

To study the effect of mining production on the return to education, we estimate mincer-like equations, using educational levels as independent variables rather than years of education. We define educational levels in the following way: first, "Primary" takes the value of 1 whether the individual "$\imath$" completed primary education, and 0 otherwise. The variable "High-School" takes the value of 1 whether he individual "$\imath$" completed secondary education, and 0 otherwise. Finally, the variable "Post-Secondary" takes the value of 1 whether the

[10] In Table A1 we show that neither hourly wages nor monthly working hours are affected by the mining production.

individual ”ı” completed post-secondary education (i.e. university or technical studies). We include all these variables and their interaction with $Q_{j,t-1}$, the lagged mining production of district ”ȷ”. Hence the variable ”Production x Post-Secondary” shows how the return to post-secondary education is affected by the mining production relative to high-school.

Table 3: The Effect of Mining Production on the Return to Education

	Log Hourly Wages				
	Standard Mincer Equation	With Quartic Function in Experience	With Cohort F.E and Educ. Q. Trends	With Province L. Trends and Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)	(5)
Lagged Production	0.00048	0.00046	0.00040	0.00029	0.00023
	(0.00089)	(0.000889)	(0.00086)	(0.00099)	(0.00095)
Production x Prim	-0.00028	-0.00025	-0.00036	-0.00020	-0.00031
	(0.00068)	(0.00068)	(0.00067)	(0.00069)	(0.00068)
Production x Sec	-0.00024	-0.00024	-0.000078	-0.00016	-0.00001
	(0.00066)	(0.00067)	(0.00069)	(0.00067)	(0.00069)
Production x Post-Sec	-0.000641***	-0.000636***	-0.000560***	-0.000650***	-0.000571***
	(0.000146)	(0.000146)	(0.000138)	(0.000143)	(0.000135)
Dep. Var.	0.967	0.967	0.967	0.967	0.967
A. R^2	0.326	0.327	0.337	0.330	0.341
Districts	1521	1521	1521	1521	1521
Obs	341838	341838	341838	341838	341838
t FE	X	X	X	X	X
District FE	X	X	X	X	X
Controls	X	X	X	X	X
L. Trends				X	X
Region-t FE				X	X

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

On Table 3 we show the results. Under column (1) we run a standard mincer equation: we include a quadratic polynomial in potential experience (defined as individual’s age minus the number of years of education minus 5), a dummy indicating whether the individual is women, a dummy indicating whether the individual’s maternal language is quechua, a dummy indicating whether the individual lives in a rural district, the number of household members, a dummy indicating whether the household head is women and a linear term in mining canon. Under column (2), as suggested by Heckman, Lochner and Todd (2003), we augment the above specification by including a quartic polynomial expression in experience, and the interaction of this expression's each term with each of the educational level dummies defined above. Under column (3), we include cohort fixed effects and a full quadratic polynomial interacted with each educational level dummy.[11] Furthermore, under column (4) we include province-specific linear trends and region-year fixed effects. Last but not least, under column (5) we include all the terms included in (2), (3), and (4) simultaneously.

Table 3 shows that, independently of the specification used, the return to post-secondary education decreases with respect to secondary education. Atkin (2016) and Edmonds, Pavnik and Topalova (2010) also explore whether changes in the return to education explain changes in enrollment. However, the main driver behind their results is explained by the cost of opportunity channel and the income channel, respectively. On the other hand, Cascio and Nayaran (2015) show that fracking increased high-school drop rates of male teens by increasing the returns to high-school education, which is a similar to our findings (they study high-school education, where we study post-secondary education). On the contrary, Toews and Libman (2017) show the resource boom in Kazahkstan increased both employment opportunities for the educated and the demand for education.

Furthermore, we carry out an exercise of falsification. Since we are stating that changes in the return to post-secondary education -and not changes in the return to high-school education- are inducing individuals to interrupt their studies, then the probability of dropping from high-school should remain unaffected. Thus, we estimate the effect of mining production on the probability of continuing with secondary studies in a similar fashion as in Panel A from Table 2. Results are reported in Table A2: the probability of continuing with secondary studies is not affected by mining production. Since we observe that the return to higher education is decreasing -and not the return to high school education-, it makes perfect sense that we observe a fall in the probability of continuing with post-secondary

[11] Also, as suggested by Heckman, Lochner, and Tood (2003).

studies and a null effect on the probability of continuing with high-school education.

6.2 Income and Wealth

Recall from our discussion in Section 3 that if mining booms increases the available income for households, and if education is a normal good, households may decide to send their children to school (or in this case, their teen sons to a higher education institution, see Lovenheim, 2011; Dahl and Lochner, 2012; Bulman et al., 2016). Hence, in this section we test whether mining production increases household's income.

We estimate equation (1) using household income, household expenses, and the self-reported hypothetical rents as dependent variables. Results are shown in Table 4. All in all, it seems that income is not playing a big role. Although, according to column (1), household income increases with mining production, the estimation is not robust to every specification (refer column 2, 3 and 4). Moreover, other measures of wealth (i.e. expenses and rents) does not seem to be affected by mining production. This is in contrast with the findings of Aragon and Rud (2013): they find that income increases thanks to gold production.[12]

6.3 Health

Many papers have shown that healthy kids have better educational outcomes. For instance, Aldeman et al. (2001) employs longitudinal data to study how child health affects school enrollment in rural Pakistan. They show that child health is linked with a higher probability of enrollment (refer to Glewwe (2005) for a review of the literature). Thinking in our theoretical background from Section 3, we can rationalize the relationship between health and enrollment as a physical cost. If health is deteriorated, then it will be more costly for students to study.

[12] It is important to note that Aragon and Rud state that the positive impacts on income and health that they found may be related to a change in policy within the mine they studied. They state that Yanacocha changed their local procurement policy, favoring the purchase of local inputs.

Table 4: The Effect of Mining Production on Income, Expenses and Rents

	With Covariates	With HH. Covariates	With Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)
Panel A: Log of Household Total Income				
Lagged Production	0.000343	-0.0000170	-0.000115	-0.0000140
	(0.000486)	(0.000314)	(0.000301)	(0.000284)
Mean of Dep. Var.	10.23	10.23	10.23	10.23
Adjusted R^2	0.383	0.485	0.491	0.493
Districts	1348	1348	1348	1348
Observations	35109	35023	35023	35023
Panel B: Log of Household Total Expenses				
Lagged Production	0.000432	0.0000909	0.0000328	0.0000768
	(0.000342)	(0.000287)	(0.000277)	(0.000267)
Mean of Dep. Var.	10.14	10.14	10.14	10.14
Adjusted R^2	0.461	0.592	0.599	0.602
Districts	1348	1348	1348	1348
Observations	35109	35023	35023	35023
Panel C: Log of Hypothetical Rents				
Lagged Production	0.000709	0.000718	0.000576	0.000664
	(0.000839)	(0.000793)	(0.000682)	(0.000597)
Mean of Dep. Var.	4.959	4.958	4.958	4.958
Adjusted R^2	0.582	0.631	0.638	0.640
Districts	1342	1342	1342	1342
Observations	32095	32022	32022	32022
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
L. Trends				X

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.

Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: The Effect of Mining Production on Health

	With Covariates	With Province Linear Trends	With Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)
Panel A: Acute Diseases				
Lagged Production	0.000417**	0.000347	0.000277	0.000321
	(0.000200)	(0.000211)	(0.000225)	(0.000253)
Mean of Dep. Var.	0.518	0.518	0.518	0.518
Adjusted R^2	0.0454	0.0463	0.0579	0.0580
Districts	1348	1348	1348	1348
Observations	35083	34997	34997	34997
Panel B: Chronic Diseases				
Lagged Production	0.000497**	0.000548***	0.000533***	0.000529***
	(0.000205)	(0.000207)	(0.000189)	(0.000180)
Mean of Dep. Var.	0.209	0.209	0.209	0.209
Adjusted R^2	0.0587	0.0636	0.0702	0.0695
Districts	1348	1348	1348	1348
Observations	35083	34997	34997	34997
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
L. Trends				X

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

We construct two indicators for health status. The first one, "Acute Disease" takes the value of 1 if individual "i" reports having any acute disease (such as a flu), and 0 otherwise. The second indicator, "Chronic Disease", takes the value of 1 if individual "i" reports having a chronic disease, and 0 otherwise.

In contrast with the findings of Aragon and Rud (2013), individuals are becoming sicker with mining production (see Table 5). The probability of suffering an acute disease increases in 0.04 percentage points for every real US$ 1000 increase in mining production per capita. Given that, in average, per capita mining production has increased in real US$ 20 thousands in our period of analysis, that means the probability of suffering an acute disease has increased in almost a percentage point in mining districts, relative to non-mining districts. However, this relationship loses statistical significance when we include background covariates, region-year fixed effects or linear trends. On the other hand, results over the probability of suffering a chronic disease increases in a similar magnitude but robust to these specifications. From 2004 to 2016, chronic diseases have increased in more than 1 percentage point in mining areas relative to non-mining areas.

These results suggest that health may be a relevant mechanism driving the decrease in the probability of continuing with post-secondary studies. However, recall that according to Table A2, mining production does not decrease the probability of continuing with high-school. When we estimate similar regressions as the ones in Table 5 but for the high-school population (see Table A3), we find that they are also getting sicker, which suggests that health is not the main driver behind our results.

6.4 Labor Reallocation within Household

Another channel that may explain our results is related to parental work. We have shown that employment opportunities for the young are unaffected by mining production. However, mining could also foster or hinder adults' employment opportunities. If education is a normal good, jobs for the parents are equivalent to having more money, which in turn should increase schooling.

To test the impact of mining production on parents' employment, we estimate an equation similar to (1) but using work dummies for each parent as dependent variables. We also use hourly wages and the amount of hours worked in the last month. Results are reported in Table 6. We show that, fathers' employment opportunities are almost unaffected by mining production. However, female labor opportunities are enhanced: given that from 2003 to 2015, mining production per capita increased in real US$ 20 thousands, mothers' employment rose by more than 2.2 percentage points in mining districts relative to non-mining districts.[13] Similarly, mothers' productivity (i.e. wages per hour) increased in almost 10%

[13] Unreported results show that mothers' employment in non-mining district increased in about 6 percentage points during this period. This means that in mining-districts, mothers' employment increased in at

during the same period.[14]

Table 6: The Effect of Mining Production on Parents' Labor Outcomes

	Father's Labor Outcomes			Mother's Labor Outcomes		
	Employment	Log Hourly Wage	Monthly Hours	Employment	Log Hourly Wage	Monthly Hours
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged	-0.000145	0.000408	-0.0344	0.00114***	0.00479**	-0.0813
Production	(0.000157)	(0.000638)	(0.0543)	(0.000240)	(0.00199)	(0.205)
Mean of Dep. Var.	0.933	1.541	184.8	0.743	0.943	154.1
Adjusted R^2	0.0764	0.378	0.0890	0.0755	0.0796	0.0586
Districts	1348	1307	1344	1348	1086	1115
Observations	35023	28679	31642	35023	18993	20806
t FE	X	X	X	X	X	X
District FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X
HH. Controls	X	X	X	X	X	X
Region-t FE	X	X	X	X	X	X
L. Trends						

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Given that employment is increasing for mothers, to explain the reduction in schooling, we should find that adults who previously were looking after the young in the household, are now entering the workforce and making the youth stay at home, as in Atkin (2016). In other words, we should find that the interaction term between the work dummy and mining production is negative. In Table 7, we report the results of running a regression including work dummies and their interaction with mining production. We can see that the impact of mining is smaller in absolute value when either the father or the mother works. When introducing a full quartic function of income interacted with i) father's and mother's work

least 8 percentage points.

[14]In Table A4 we show how changes over fathers' and mothers' employment are decomposed across different sectors. In particular, we see that fathers are getting out from the industry sector and are going to the services sector and into unemployment. On the other hand, Mothers are getting out from unemployment and are getting into the services sector and commerce.

dummies and ii) our variable of interest, the coefficients (from column 1 to column 3) are similar except for the coefficient of the interaction term between mining production and the father's work dummy, which becomes smaller and insignificant (P=11.0%).[15] This suggest that the alleviating effect of parental work is not only driven by higher income, but perhaps by other channels such as a larger share of bargaining power falling into mothers (recall that mothers are increasing their employment and opportunity, see Aizer (2010)).

All in all, results from Table 6 and Table 7 suggest that the parental work channel does not explain our results. If anything, this channel alleviates the negative effect of mining on the probability of continuing with post-secondary studies.

Table 7: The Effect of Mining Production by Labor Parents

	Prob. of Following Post-Secondary	Prob. of Working in Paid Job	Prob. of Being Idle
	(1)	(2)	(3)
Lagged Production	-0.00131***	-0.000624**	0.000528***
	(0.000400)	(0.000262)	(0.000197)
Lagged Production x	0.000525***	0.000242**	-0.000195***
Father Works	(0.0000896)	(0.000110)	(0.0000472)
Production x	0.000257*	0.000131	0.000106**
Mother Works	(0.000133)	(0.000101)	(0.0000429)
Mean of Dep. Var.	0.445	0.451	0.151
Adjusted R^2	0.144	0.111	0.151
Districts	1348	1348	1348
Observations	35023	34970	35002
t FE	X	X	X
District FE	X	X	X
Controls	X	X	X
HH. Controls	X	X	X
Region-t FE	X	X	X
L. Trends			

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

[15] Results not shown. Available upon request.

7 Robustness

7.1 Migration

Endogenous migration could explain our results if households with a lower propensity to send their children to higher education in-migrate towards mining areas (i.e. the effect on migrants would be higher), or if households with a larger propensity to send their children to higher education out-migrate towards non-mining areas (i.e. the effect on migrants would be lower). Conversely, our results would be downward biased if households with a larger propensity to send their children to higher education in-migrate towards mining areas (i.e. the effect on migrants would be lower), or if households with a smaller propensity to send their children to higher education out-migrate towards non-mining areas (i.e. the effect on migrants would be higher).

In Table 8, we estimate a similar equation as in (1) but with the addition of the interaction between mining production and a dummy indicating whether individual "i" have ever migrated from one district to another one. We find that part of our results is driven by stayers. This means that in-migration is not a concern: if anything, in-migration would be downward biasing our results. However, out-migration could be biasing our estimations. In any case, the effect is significant for both, stayers and migrants.[16] This alleviates our concern regarding endogenous migration.

We also test whether mining influences the composition of individuals living in mining districts. We think that changes in these demographics are mostly caused by migration patterns. According to Table A5, the proportion of migrants is increasing in mining areas relative to non-mining areas. The estimated coefficient implies that from 2004 to 2016 the proportion of migrants in mining districts have increased in at least 1 percentage point. Since the effect of mining on schooling is attenuated on migrants, and the proportion of migrants is increasing in mining areas, these two facts suggest that, if anything migration patterns are downward biasing our results: households with a larger propensity to send their children to higher education are in-migrating towards mining areas (i.e. the effect on

[16] We tested the null hypothesis that -0.000714 + 0.000287 = 0, and we rejected it.

migrants is lower and the net flow of in-migrants is positive).

We also explore whether there is other compositional changes and we find that parents are a little bit less educated in mining areas relative to non-mining areas. Even though this difference is statistically significant for fathers, its economic relevance is small: from 2004 to 2016, our estimated coefficient implies a change of -0.05 years of education. We also find that parents are getting older in mining areas: our estimated coefficient imply that, from 2004 to 2016, fathers and mothers are at least 0.2 and 0.14 years older in mining areas relative to non-mining areas. In unreported results, we find that a higher parental age is positively linked with the probability of continuing with studies. Thus, this compositional change caused by migration would be downward biasing our results.

We also show that the average birth order (i.e. whether they were the first, the second, or the third son, and so on) is getting larger: on average individuals from our sample were ranked 0.2 higher in mining areas relatively to non-mining areas. We also find that the average number of boys living in the household is getting higher in mining areas. However, nor birth ranking nor the number of boys are significantly related to the probability of continuing with post-secondary studies. Finally, we find some differences in the number of household members (from 2004 to 2016, our coefficient implies that the number of members increased in 0.052 members), the proportion of female students (our coefficient implies a change of -0.76 percentage points from 2004 to 2016), and students' age (students are getting 0.07 years older) in mining area relatively to non-mining areas. Given that these variables are negatively, positively and negatively linked with the probability of continuing with post-secondary studies respectively, these compositional changes are upward biasing our results (in absolute value). However, differences are small, thus the bias should be small too.

Table 8: The Effect of Mining Production by Migration Status

	Prob. of Following Post-Secondary	Prob. of Working in Paid Job	Prob. of Being Idle
	(1)	(2)	(3)
Lagged Production	-0.000714**	-0.000126	0.000466***
	(0.000289)	(0.000192)	(0.000179)
Lagged Production x	0.000287***	0.00000236	-0.000103**
Migration	(0.0000341)	(0.0000650)	(0.0000462)
Mean of Dep. Var.	0.445	0.451	0.151
Adjusted R^2	0.144	0.103	0.148
Districts	1348	1348	1348
Observations	35023	34970	35002
t FE	X	X	X
District FE	X	X	X
Controls	X	X	X
HH. Controls	X	X	X
Region-t FE	X	X	X
Linear T.			

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

8 Conclusions

This paper makes several contributions to the literature. First, we focus on higher education, topic that, relative to high school, is understudied by the literature of natural resources. To the best of our knowledge, this paper would be one of the first in studying specifically the link between the boom of natural resources and higher education interruption. Second, we show that mining booms can affect the return to education, thereby, creating incentives for individuals to interrupt their studies. Third, we provide evidence of other mechanisms that usually the literature has neglected, such as health and labor reallocation within household.

Our results show that mining production have a significant and robust impact on the probability of continuing with post-secondary studies and an increase in the probability of staying idle. This decrease is driven mainly by a decrease in the return to higher education and not by a increase in the cost of opportunity of studying. Other alternative mechanism that may be explaining part of our results is the increasing health problems our sample reports as a consequence of mining production. Other mechanisms, such as labor reallocation within household seem to be lessening the problem.

There is a large potential for future research. In particular, we have observed a negative effect on enrollment, a short-term measure. However, we do not know the impact of mining production on the long run. It is possible that individuals may come back to study long after they interrupt their studies. For example, an individual may build up her resources by working on the labor market, and then come back to finish their education.

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Appendix

Appendix 1

Table A1: Nor wages nor hours worked are affected.

Table A1: The Effect of Mining Production

	With Covariates	With HH. Covariates	With Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)
Panel A: Log Hourly Wages				
Lagged Production	0.00313**	0.00216	0.000829	0.000792
	(0.00135)	(0.00168)	(0.00146)	(0.00157)
Mean of Dep. Var.	0.985	0.985	0.985	0.985
Adjusted R^2	0.227	0.237	0.241	0.242
Districts	1037	1037	1037	1037
Observations	10782	10768	10768	10768
Panel B: Monthly Hours Worked				
Lagged Production	-0.120	-0.0367	0.162	0.189
	(0.336)	(0.297)	(0.358)	(0.381)
Mean of Dep. Var.	139.6	139.6	139.6	139.6
Districts	1050	1050	1050	1050
Adjusted R^2	0.0380	0.0554	0.0585	0.0597
Observations	11383	11366	11366	11366
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
Linear T.				X

Appendix 2

Table A2:

Table A2: The Effect of Mining Production on the Probability of continuing with secondary studies

	With Covariates	With Province Linear Trends	With Regional F.E.	Full Specification
	(1)	(2)	(3)	(4)
Lagged Production	-0.000078	-0.000081	-0.000073	-0.000092
	(0.00018)	(0.00018)	(0.00018)	(0.00017)
Mean of Dep. Var.	0.815	0.815	0.815	0.815
Adjusted R^2	0.679	0.681	0.682	0.684
Districts	1492	1492	1492	1492
Observations	85525	85427	85427	85427
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
L. Trends				X

Appendix 3

Table A3: The Effect of Mining Production on Health of High-School Students

	With Covariates	With Province Linear Trends	With Regional-Year F.E.	Full Specification
	(1)	(2)	(3)	(4)
Panel A: Acute Diseases				
Lagged Production	0.0000230	0.0000289	-0.00000710	0.000165
	(0.000360)	(0.000360)	(0.000367)	(0.000294)
Mean of Dep. Var.	0.499	0.499	0.499	0.499
Adjusted R^2	0.0416	0.0432	0.0528	0.0547
Districts	1492	1492	1492	1492
Observations	85493	85396	85396	85396
Panel B: Chronic Diseases				
Lagged Production	0.000610**	0.000593**	0.000576**	0.000515*
	(0.000253)	(0.000254)	(0.000246)	(0.000279)
Mean of Dep. Var.	0.118	0.118	0.118	0.118
Adjusted R^2	0.0550	0.0606	0.0675	0.0677
Districts	1492	1492	1492	1492
Observations	85493	85396	85396	85396
t FE	X	X	X	X
District FE	X	X	X	X
Controls	X	X	X	X
HH. Controls		X	X	X
Region-t FE			X	X
L. Trends				X

Source: National Household Survey (2004-2016), Ministry of Energy and Mines, Ministry of Economics.
Notes: Standard Errors clustered at the district level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix 4

Table A4: Men are loosing their job in industry and are starting to work in services, but, in total, employment decreases. For women, they are starting to work in commerce and in services.

Table A4: The Effect of Mining Production on Employment by Sectors

	Total Employment	Sector				
		Agriculture	Industry	Commerce	Construction	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Father						
Production	-0.000198**	-0.0000387	-0.000753***	-0.0000463	0.000106	0.000564***
	(0.0000991)	(0.000156)	(0.000205)	(0.0000593)	(0.000116)	(0.000106)
Production Standarized	-0.00808	-0.00158	-0.0307	-0.00189	0.00431	0.0230
Mean of Dep. Var.	0.933	0.250	0.104	0.0964	0.188	0.298
Adjusted R^2	0.0764	0.503	0.0719	0.0300	0.0711	0.197
N. Districts	1353	1353	1353	1353	1353	1353
Observations	35955	35952	35952	35952	35952	35952
Panel B: Mother						
Production	0.00105***	0.0000779	0.000000681	0.000285*	0.0000571***	0.000637***
	(0.000130)	(0.000121)	(0.0000897)	(0.000159)	(0.0000161)	(0.000188)
Production Standarized	0.0427	0.00318	0.0000277	0.0116	0.00233	0.0260
Mean of Dep. Var.	0.742	0.190	0.0641	0.234	0.0124	0.274
Adjusted R^2	0.0754	0.464	0.0361	0.0484	-0.000649	0.126
N. Districts	1353	1353	1353	1353	1353	1353
Observations	35955	35955	35955	35955	35955	35955
Year FE	X	X	X	X	X	X
District FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X
Linear Trends	X	X	X	X	X	X
Region-Year FE						

Appendix 5

Table 5: Compositional Changes caused by Mining

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A:									
	Migration	Educ (F)	Educ (M)	Quechua (F)	Quechua (M)	Age (F)	Age (M)	Female Head	Firstborn Boy	Birth Order
Lagged Production	0.000535***	-0.00243*	-0.00160	-0.0000342	-0.0000676	0.0111***	0.00741***	0.0000868	-0.0000506	0.00118*
	(0.000183)	(0.00140)	(0.00184)	(0.000229)	(0.000246)	(0.00356)	(0.00272)	(0.0000667)	(0.000208)	(0.000639)
Mean of Dep. Var.	0.431	10.36	8.720	0.285	0.275	51.11	47.22	0.0449	0.517	2.025
Adjusted R^2	0.307	0.226	0.259	0.467	0.484	0.0571	0.0692	0.0171	0.0155	0.0639
Districts	1358	1358	1358	1353	1353	1358	1358	1358	1358	1358
Observations	37164	37122	37143	36036	36049	37163	37164	37164	37164	37164
	Panel B:									
	# Girls	# Boys	# Members	Female	Quechua	Rural	Public	Age	Canon	
Lagged Production	0.000548	0.00124**	0.00251*	-0.000380**	-0.0000303	0.000157	0.000164	0.00345***	0.000842	
	(0.000469)	(0.000597)	(0.00144)	(0.000184)	(0.000120)	(0.000213)	(0.000192)	(0.00130)	(0.00131)	
Mean of Dep. Var.	1.467	1.570	5.499	0.485	0.0842	0.229	0.407	20.19	0.0458	
Adjusted R^2	0.0691	0.0912	0.121	0.0123	0.507	0.681	0.138	0.0464	0.895	
Districts	1358	1358	1358	1358	1353	1358	1358	1358	1353	
Observations	37164	37164	37164	37164	36043	37164	37162	37164	36232	
District & Year FE	X	X	X	X	X	X	X	X	X	X
Controls										
HH. Controls										
Region-Year FE	X	X	X	X	X	X	X	X	X	X
Linear T.										