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The Heterogeneous Local Labour Effects of Mining Booms

Edgar Salgado Chavez

Department of Economics, University of Sussex, UK
Science Policy Research Unit, University of Sussex, UK
e.salgado-chavez@sussex.ac.uk

Abstract: Using two rounds of population census for 1043 districts in Peru I document that large-scale mining activity had a positive effect on local employment over 14 years. The effect is differentiated by industry, skill and migration status. Employment grew by 0.04 percentage points faster by one standard deviation increase in the mineral prices. Both high and low skilled workers enjoyed similar employment increase, however only low skilled workers experienced a decline in unemployment. Using data from 10 annual household surveys I find that, consistent with a model of heterogeneous firms and labor, wages for low skilled workers in districts close to the mining activity was 0.05 percentage points higher by every standard deviation increase in the index of mineral prices. Additional evidence with the census data suggests that locals working in the mining or the agricultural sector filled the new employment opportunities. More evidence suggests that mobility costs and not the elasticity of substitution between high and low skilled workers or skill acquisition may explain the outcome. Together these findings suggest that large-scale mining activity increases the demand for mining and agricultural local employment, and the wages in the local economy.

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Using two rounds of population census for 1043 districts in Peru I document that large-scale mining activity had a positive effect on local employment over 14 years. The effect is differentiated by industry, skill and migration status. Employment grew by 0.04 percentage points faster by one standard deviation increase in the mineral prices. Both high and low skilled workers enjoyed similar employment increase, however only low skilled workers experienced a decline in unemployment. Using data from 10 annual household surveys I find that, consistent with a model of heterogeneous firms and labor, wages for low skilled workers in districts close to the mining activity was 0.05 percentage points higher by every standard deviation increase in the index of mineral prices. Additional evidence with the census data suggests that to a large extent locals working in the mining or the agricultural sector filled the new employment opportunities. More evidence suggests that mobility costs and not the elasticity of substitution between high and low skilled workers or skill acquisition may explain the outcome. Together these findings suggest that large-scale mining activity increases the demand for mining and agricultural local employment, and the wages in the local economy.

1 Introduction

Over the past decade commodity prices boomed to the benefit of many countries endowed with natural resources. When a producing country experiences a price boom, revenues increase from a macro perspective and GDP also booms, mainly fueled by higher revenues. However, from a micro perspective, it is not clear who gains from the mining boom or what are the linkages with other industries. Large scale mining is generally regarded as an industry with little contribution to the local labor market due to its high dependency on capital. This concern is of course, particularly relevant in a country whose main activity is mining.

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The goal of this chapter is to provide an understanding of the degree of connection between the natural resources sector and other industries. The way I analyze this connection is through the local labor markets.

This chapter, therefore, merges two streams of literature: one that understands the interactions within the local labor markets and one that is permeated with the idea of the "Natural Resource Curse", or "Dutch Disease". The current emergence of the literature on local labor markets has prompted a set of new tools that take the city or any other small geographical unit as the piece of observation, and naturally links the response of labor variables to local demand or productivity shocks.

In particular, the literature on local labor markets tries to understand the local effects of a local demand shock on employment, population and wages (Moretti; 2010, Notowidigdo; 2013), and its interaction with any policy intervention (Kline and Moretti; 2014). Moretti (2011) offers a coherent framework based on the works of Roback (1982), Topel (1986), Bartik (1991) and Blanchard and Katz (1992) that motivates further developments. In particular, the author provides the theoretical framework to understand the effects of a productivity shock in local markets. In his formulation, the effect come as a consequence of the interaction of labor and housing markets in a context where individuals take decisions based on the wage differences across cities. Empirically, Moretti (2010) proposes an estimation strategy based on the Bartik type of shocks[1] to understand the creation of jobs in the non-traded sector as a consequence of a demand shock in the traded sector. Notowidigdo (2013) develops a theoretical model to explain the effect of local demand shocks conditional on the degree of mobility attributed to different types of labor. Theoretically, the author contributes to the discussion by including two types of workers: high skilled and low skilled. His estimates suggest that low skilled workers react less to local demand shocks. Kline and Moretti (2014) also develop a theoretical model to understand the impact of local based interventions. One extension of their theoretical model relates the effect of productivity shocks to agglomeration.

More recently, Alcott and Keniston (2015) develop a theoretical model to evaluate the local impact of a shock in the natural resource industry given its links to intermediate industries and local firms. Their model is tested with data from the United States and assumes, however, only one type of labor. The theoretical framework developed in this chapter draws inspiration from this study.[2]

On the other hand, the literature on the "Natural Resource Curse" or "Dutch Disease"[3] has traditionally taken a macro perspective. At the macro level, the effects of a Dutch Disease

[1]The original idea belongs to Bartik (1991). A Bartik instrument exploits the differences in the industry composition across cities compared to the national industry composition. The source of the identification comes from the interaction of the national growth rate of the industries with the industry shares at the city level. A notable application for the housing markets in the U.S. can be found in Guerrieri et al. (2013).

[2]Which, is also related to the preliminary discussion about the interaction between tradable and non-tradable industries presented in Moretti and Thulin (2013)

[3]Ideas championed by Jeffrey Sachs and Andrew Warner in the nineties (Sachs and Warner; 1995, Sachs and Warner; 1999)

can be listed as: (i) real exchange rate appreciation, (ii) fall in manufacture production (iii) fall in the profits for the traded manufacturers. The availability of data at a smaller geographical level allows to re-visit this literature through the lenses of the local labor markets[4]. Beyond the question whether the abundance of natural resources is good or not for long-run growth, the question about the mechanisms operating within the country is equally relevant. What are the local effects of a boom in oil or mineral production? Recent empirical studies at the micro level have attempted answers to these questions. Black et al. (2005) evaluate the impact the coal mining boom, peak and bust for a group of producing cities in the United States. This chapter draws empirical inspiration from this work, but extends the analysis to the national level and by type of labor.

In the developing country setting, much effort has been placed on identifying short-term impacts, but there is a lack of evidence on the long-term impact or the heterogeneity of the response by the type of worker, as well as a better documentation of the channels. Aragón and Rud (2013), another work from which I draw empirical inspiration, explore the backward linkages of a demand shock from a gold mine. The authors build upon the framework in Moretti (2010) to explore local multipliers and find that the mining local purchases impact positively local income. In this chapter I take a finer look at the labor markets and focus on wages instead of household income.

Fafchamps et al. (2015) propose a broad empirical model to understand the booming gold activity in Ghana. Using night lights data, the authors conclude that mining shocks can predict proto-urbanization in the area surrounding the mine. Interestingly, they also find that the results are not reversed once the mine is closed. Loayza et al. (2013) studies the effect of mining on poverty and inequality at the local level in Peru, and find that an increase in the local revenues derived from the mining activity is associated with lower levels of poverty but higher consumption inequality.

This chapter seeks to contribute by proposing an empirical strategy to address the main implications related to the effect of mining booms at the local level. I use a sample of 1043 districts from Peruvian highlands that were close to a mine in 1993 and observe their employment and population response following a boom in the mineral prices from 1993 to 2007. Other things equal, districts close to the mine and those in the surrounding area can be comparable. The challenge consist, precisely, on gathering the appropriate control group for comparison.

As a preview, results suggest that large-scale mining activity boosted total employment in the local economy, which is constituted by the set of districts within a 100km distance to the mine. Both, high skilled and low skilled employment rates grew as a result of this. Wages in the mining area increased, and such increase was focused in agricultural earnings. This result provides enough evidence to conclude that mining booms affect local agricultural

[4] Although the effect on real exchange rate seems inherently embedded in the macro perspective, it is easily implemented at the local economy, since the real exchange rate can be expressed as the ratio between the prices for traded goods and non-traded goods.

economies through the *spending effect* as outlined by Corden and Neary (1982). The point estimates for the effect on low skilled wages are higher than the point estimates for the effect on high skilled wages, but they are not statistically different. Finally, the faster increase in the employment rate was explained by a faster increase in the employment rate of locals rather than migrants. This effect is also heterogeneous by industry: high skilled locals fill the new mining employment opportunities, while low skilled locals explain the increase in agricultural employment.

For the remainder, this chapter is organized as follows: section 2 defines the theoretical framework to guide the analysis. Section3 details the data used in the analysis, explains the selection of the districts and specifies the identification strategy. Section 4 presents the results. Finally section 6 concludes.

2 Conceptual Framework

The theoretical basis for the analysis is grounded on the local labor markets literature (Moretti; 2011). In this section I develop a narrative to guide the empirical results. The idea behind is the existence of heterogeneous firms that use the same technology but respond differently to productivity shocks in the natural resources industry, and demand different types of labor.

The unit of analysis is the district or locality where different types of firms operate. Firms may belong to different groups: natural resources, tradable and non-tradable. Natural resource firms sell their output in the international markets for mineral commodities. Firms in the tradable sector sell in the national, local or international markets[5]. Firms that operate in the local economy, i.e. firms in the non-tradable sector sell locally. Non-tradable sector is comprised by all other firms with the exception of government. These three types of firms compete for two types of workers in the locality: high skilled workers (H_i) and low skilled workers (L_i), who receive different wages: w_H and w_L. The national population, Pop, is fixed, so changes in the district population come in the form of people moving from one city to the other depending on the relative city wages. The national stock of high skilled H and low skilled L workers is also fixed.

In a setting like this, it is possible to think of workers, who supply labor, maximize their utility depending on aggregate wages for their type, amenities and a their location preference (also depending on their type).[6] Consequently, the location preference can also be understood as mobility cost[7]. The idea is simple, high skilled individuals may exhibit less attachment to cities and therefore their location preference is less rigid, less strong, which ultimately can also be understood as lower mobility costs.[8]

[5]Tradable sector could be constituted by manufacture and agriculture firms.

[6]For instance, Moretti (2011) differentiates the utility derived from amenities by each type of labor.

[7]As in Notowidigdo (2013)

[8]Notowidigdo (2013) provides an insightful discussion about the location preferences. High preferences for one location, or high migration costs, imply a less responsive labor supply. If location preferences are irrelevant

Labor demand, on the other hand is determined by firms. Firms demand labor locally through the maximization of their profits. Each sector combines capital and a labor, where labor is combined assuming some degree of substitution between high and low skilled workers.

It is also possible to think that all industries are affected by productivity shocks in the natural resource sector. As in Alcott and Keniston (2015), the natural resources sector impacts other industries via the change in revenues. An increase in local revenues derived from the boom in the natural resources sector can be interpreted as a demand shock for the the industry selling locally. To the degree that the local manufacture industry produces intermediate good used as inputs by the natural resources sector, the boom in the mining sector also creates a demand shock for the manufacture producers. Moretti and Thulin (2013) provide another useful theoretical discussion which highlights the connections among sectors. In particular, the authors highlight the relevance of migration costs in the determination of wages.

Empirically I will evaluate the labor demand shock as a ***price shock*** in the natural resource sector: a productivity shock in the natural resources sector represents in income shock for workers in that industry, who happen to live locally. The increase in their rents spills over the local economy through consumption of local goods, which increases prices and the rents of the non-tradable or service sector. The same explanation is less clear for the tradable sector. Its tradable nature implies that the prices they receive do not change, and on the contrary, the costs they face may increase, if the wages of the workers they employ increase, which will represent a negative shock. However, it is also possible that there are linkages between the natural resources sector and the tradable, which ultimately would imply a positive spillover.

Equilibrium in the labor market takes place when labor demand and supply intersect. If the mobility cost of high skilled workers is smaller than the mobility cost of low skilled workers and for a given elasticity of substitution between high and low skilled workers, employment in the high skilled sector should increase faster than employment in the low skilled segment of workers following a productivity shock in the natural resource sector.

The response of wages to the shock in the natural resource sector depends on the location preferences by each type of worker and the elasticity of substitution between high and low skilled workers. In the extreme case that both types of workers have the same location parameters or mobility costs, their wage response is identical, regardless of the elasticity of substitution. Depending on the differences in the location preferences, the impact on wages varies.

If high skilled workers are more mobile than low skilled workers, the initial push on wages, is offset by the differential labor supply response, and wages for the low skilled workers should increase. However, this balancing force is attenuated by the elasticity of substitution of labor: if there is perfect substitution, the lack of mobility of low skilled workers could be compensated by high skilled workers taking up low skilled jobs which now are better paid.

or there are no mobility costs, labor supply is very sensitive to wage differences between cities.

3 Data and Identification Strategy

The empirical analysis uses 1043 districts from the highlands in Peru that I observe between 1993 and 2007. These 1043 districts were selected among the 1791 available that constitute the total number of Peruvian districts in 1994. The basic criteria for the selection sought to create a comparable set of districts in 1993, before the boom in the prices of minerals. All districts are located in the highlands of Peru, above 1,800 meters above the sea level. No large-scale mining activity is reported below 2,000 meters above the sea level. Hence, the selection process excludes relatively wealthy districts from the coast, and the relatively isolated districts from the jungle.

For the analysis I construct information at the district level about employment, population and migration by industries and skills. While for the analysis on wages I use individual level data for a sample of people living in those 1043 districts.

To estimate the impact of the boom in the mining activity, I create a measure of the boom in mineral prices. In concrete, I use information of 27 mines that were active in 1993-1994 in Peru and define a distance threshold for their influence: 100km. Every district's capital[9] whose Euclidean distance to any of the 27 mines in 1993 was smaller or equal than 100km was considered a mining district. Districts beyond that distance threshold but no more than 200km are selected as *control* group.

The unit of analysis for the variables on employment, population and migration, is the district. For wages, the unit of analysis is the individual living either in the mining or control districts. The variable of interest, the boom in the mineral prices, is measured as a compound of mines, production and prices at the district level (explained in section 3.3).

In this section I detail the data I use, as well as the empirical strategy to identify the effect of the boom in mineral prices, which led to the selection of these 1043 districts.

3.1 Data

For employment I use the population censuses of 1993 and 2007 in the estimations, and the population censuses of 1993 and 1981 to check the comparability of the districts in 1993. To estimate the effect of the boom in the mineral prices on wages I utilize data contained in the employment module from the National Household Survey (ENAHO in Spanish). This survey is collected annually from 1997 by the National Institute of Statistics of Peru. Data about mine location and production are available from InterraRMD (2013), which provides the GPS location of all large-scale mines in Peru, as well as physical production from the beginning of the 20th century in some cases. I discuss all of them in detail.

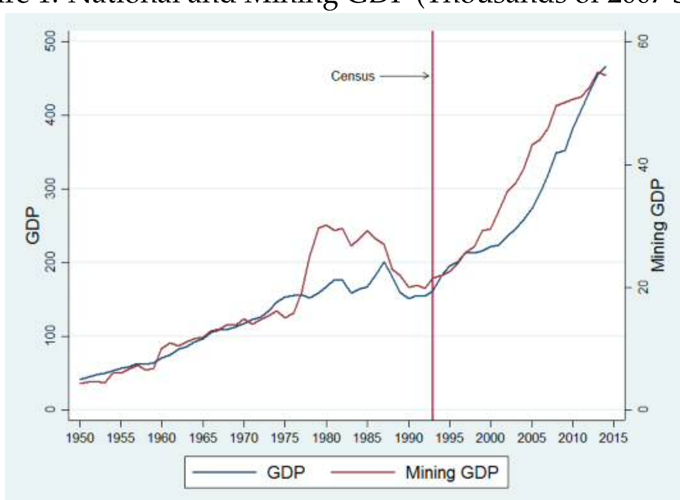
[9] I use the coordinates of the district's capital as provided by the Ministry of Education.

Mineral Data

Data about production and geographic location of mines are available from the Raw Material Data (RMD) from InterraRMD (2013). This dataset has records for 633 mine projects through the period of 1900-2014. Each mine has a GPS location that I use to measure the distance from the capital of the district to the mine. Mineral production is available on an annual basis from 1975, and by 2013 there were 367 active projects (some mines are involved in several projects).

I use 27 mines related to large-scale projects[10] for the analysis[11]. These were mines active in the baseline years 1993-1994. I use their production in 1993 to construct a weight for the change in mineral prices from 1993 to 2007. I constrain the sample to mines extracting five minerals: gold, silver, copper, lead and zinc. For each mine I, then, construct a measure of the monetary value of production in 1994 for which I use data on international prices reported by the U.S. Geological survey (see Kelly and Matos; 2013). All prices have 1994 as base year. Figure 1 shows that most of Peru's GDP is highly influenced by mining production.

Figure 1: National and Mining GDP (Thousands of 2007 Soles)



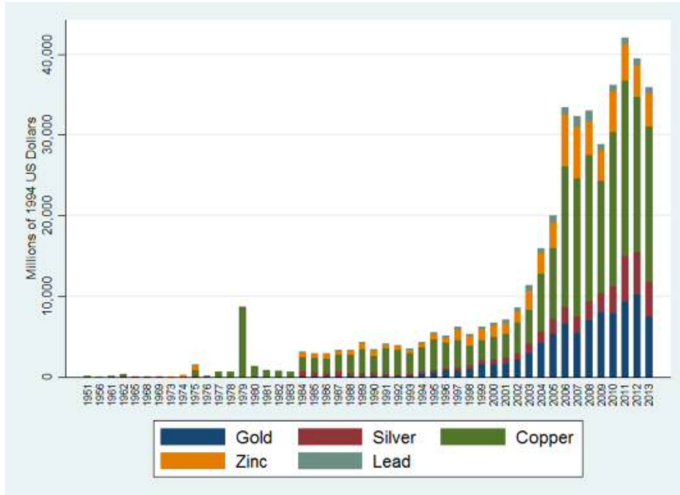
Notes: [1] Data source: Peruvian Central Bank. [2] Red line marks the beginning of the period of analysis.

The annual mining production estimated using data from InterraRMD (2013) from 1950 to 2013 and its composition is presented in figure 2. Mineral production boomed from early 2000's. Copper was by large the main mineral extracted from Peruvian mines. Gold production gained importance from middle 1990's.

[10]The data do not contain information on informal mining activity. Informal Mining remains a topic for future analysis. In some regions (which are not part of my empirical analysis) of the country, illegal gold mining boomed in recent years and has brought deforestation and other social consequences. https://www.theguardian.com/environment/andes-to-the-amazon/2016/may/01/gold-mining-in-peru-forests-razed-millions-lost-virgins-auctioned

[11]In between 1993 and 2007 41 new mines started operations, but do not include them because I am interested in the medium or long term effect of the change in mineral prices. The empirical section provides more detail on the selection process.

Figure 2: Mining Production (Thousands of 1994 US Dollars)



Notes: [1] Data source for production: InterraRMD (2013). Data source for prices: Kelly and Matos (2013).

To give an idea magnitude of the boom, from 1985 to 1995 mining production for these five minerals grew at an annual average of 3.3%. For the second half of the 1990's the average annual growth rate was 7.3%. During the 2000's the annual growth rate increased to 16%.

Census and household Data

Population censuses are collected by the National Institute of Statistics (INEI in Spanish) on an irregular basis. The last population census dates to 2007, while the closest one dates to 1993[12]. The administrative classification of Peru considered 1,791 districts in 1993. This number increased to 1,831 by 2007, but in order to retain comparability between the two censuses, for the new districts created by 2007 I assign them their administrative code as it was in 1993.

The empirical section selects a group of 1043 districts that are comparable in 1993. Ideally, they would be comparable in levels and in their trends before 1993. In order to confirm their comparability in trends, I collect information from the 1981 census. Unfortunately, the 1981 census is incomplete, and I can only use information from 22 regions out of the 25 that are in Peru[13]. This results in a reduction of the number of districts to 931 for which I am able to construct employment and population variables in 1981. In consequence, I use these 931 districts only for pre-trend checks and not for the estimation of the effect of the boom in mineral prices from 1993 to 2007.

For the information on wages I use individual level data. INEI also collects the ENAHO every year since 1997. The survey has changed through time, however it retains fixed many

[12] Both are *de facto* type of census. INEI collected a *de jure* type of census in 2005, which I do not use to avoid problems of comparability. The distinction between the two types of censuses relates to the location of the individuals at the moment of the interview. A *de jure* type of census enumerates individuals as of where they usually reside. In contrast, a *de facto* type of census enumerates the individual at the place where they were found.

[13] One of the missing regions falls within the geographic area I use for the empirical resign

of its important modules from the beginning. For the estimation of the effect of mining activity on wages I use data from the modules on education, employment and income, household characteristics, and individual characteristics. Unfortunately, the survey is statistically representative at the regional level and not at the district level. Not all the districts of Peru are covered every year, however through the sample, the different sample designs of the survey managed to collect information of all districts. In consequence, I rely on estimates at the individual level.[14]

Other data

Through the analysis I also make use of data on altitude, rainfall and land extension. Data on altitude and land extension were available from the Ministry of Energy and the agricultural census[15]. The source for the historical rainfall data is the Climatic Research Unit from the University of East Anglia[16]. I use the version TS3.20 that covers the period from January 1901 to December 2011 and provides precipitation estimates at the 5°×5° grid resolution, that I match to the district borders.

3.2 Measuring Migration

The theoretical and empirical analysis is focused on the effects of the boom in the mineral prices over the labor market: employment and wages. However, implicitly there is a migration dimension in the determination of the results.

In this brief section I outline a descriptive exercise aimed to explore with more detail the migration response. Moretti (2010) points out that the literature on local labor markets has not explored the consequences of local shocks into the the type of individual: are local residents or migrants those benefiting from the new context?

The census data typically records two questions related to migration: the district of birth and the district of residence five years ago. The combination of these two categories yields four types of individuals that live in the district. If district i's current labor force is N_i, it can be organized in four migration categories:

$$N_i = M_{i11} + M_{i12} + M_{i21} + M_{i22} \tag{1}$$

Where M_{i11} are those individuals who were born in the district and were living there also five years ago, who I term *Locals*. $M_{i12}$are individuals also born in the district but were not living there five years ago, termed as *Returned*. Individuals who were not born in the

[14]Which resembles the strategy adopted by Dell (2010) when assessing the impact of the historical institution of the mining *Mita* over household consumption in Peru.

[15]The agricultural census covers only districts with agricultural land, and therefore excludes a few districts in the coastal region with no agricultural land. This is not a problem since the identification strategy excludes districts from the coast.

[16]Available at http://www.cru.uea.ac.uk/

district but were living there since five years ago, M_{i21}, are classified as *New Locals*. Finally, individuals who were born in a different district and were also living in a different district five years ago, M_{i21}, are *New Comers*.

For each of these categories, I can also explore the response to the natural resource shock by industry and skill groups. Empirically, I explore the effects on migration of the 1043 districts I observe in the analysis. Migration, however, could be to anywhere in the country.

3.3 Empirical Framework

The unit of observation for the mining activity is the district. Ideally I would like to observe differences in the employment, population and wage variables at the district level when a district with mining activity benefits from the surge in the international prices of the minerals the firms extract. However, I can only retrieve employment and population (and migration) at the district level, while for the estimation of the effect on wages I end up using individual level data. The identification strategy selects a set of districts that are comparable at the baseline, 1993. Then it compares their response to the boom in commodity prices from 1993 to 2007.

In 1993 the 27 mines extracted the following minerals: gold, silver, copper, zinc and lead. One mine extracted the 5 minerals, 5 mines extracted 4 minerals, 11 mines extracted three minerals, 4 mines extracted 2 minerals, while 6 mines extracted only one mineral. This feature is going to be exploited in the identification strategy (i.e. each treated district was exposed not only to different number of mines but also different production of minerals by each mine).

By 2007 the number of mines had increased to 68. Although new mines offer an interesting analysis, many of them started operation between 2004 and 2006, which puts them closer in time to the end-line of the time frame, and would be more suitable for a short-term analysis. In this chapter I am interested in the medium or long-term differences. Therefore, in order to rule out any interference coming from these 41 new mines, I excluded those districts that were not under the influence of a mine in 1993 but became influenced by 2007.

In 1993, I consider that a district was under the influence of any of the 27 operating mines if the distance between its capital and any of the mines was less than 100km. This threshold is assumed in the literature and I opt for it[17]. For the estimation of the distance I use the length of the shortest curve between the coordinates of the capital of the district, and the coordinates of the closest mine[18]. I refer to them as mining districts. Then I locate districts who's capital was more than 100km apart from any of the 27 mines, but less than 200km. These are neighboring districts that could be understood as *control* group[19]. The idea is that by 1993 there were no meaningful differences in observables between districts with a mine at a 100km distance and the closest neighboring districts in the 200km radius of the mine. The choice of 100km can

[17]For instance, in a similar setting, Aragón and Rud (2013) define 100 km as the influence distance. Fafchamps et al. (2015) assume no effect of mining activity beyond 100 km.

[18]I implement this by using the STATA command `geodist`.

[19]As mentioned above, I excluded districts that were part of the control group in 1993 but became mining districts in the period following up to 2007.

also be defended by the fact that the average district in Peru has an area of 71,866 Km2 while the median district has an area of 20,852 Km2. This means that the 100 km threshold is slightly below the square root of the median area.

There were a few additional steps before reaching the final number of districts in both groups. As mentioned previously, I also excluded any district with an altitude below 1,800 meters above the sea level. The result of this is the exclusion of coast cities, and cities located in the rain-forest. There are two reasons for this. First, Peru's geography is very heterogeneous and exerts an important influence in the markets[20][21]. Second, there are no large-scale mines operating below 2,000 meters above the sea level. Therefore, the 1,800 threshold allows the inclusion of downstream cities that are still under the influence of the mining activity but somehow isolated from the coast or rain-forest dynamics.

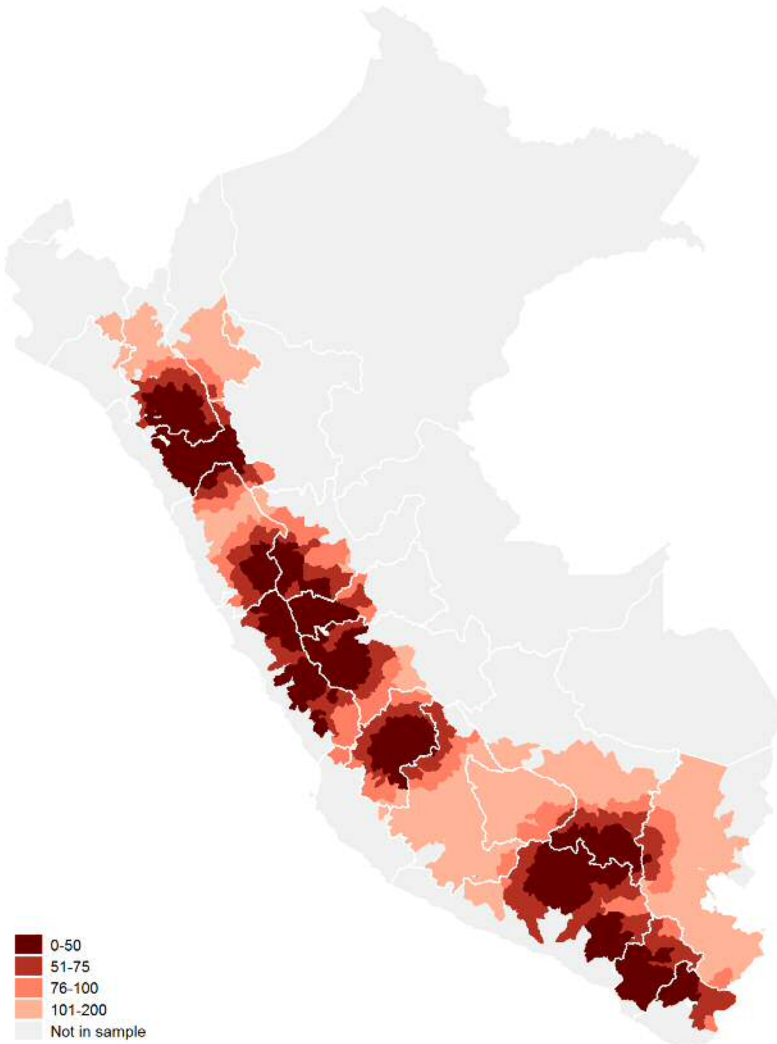
After all this criteria, the total number of districts included in the analysis was 1043. 823 districts were mining districts, within the 100km distance range from a mine, while 220 control districts were within the 101km-200km distance interval and never saw a new mine opening in subsequent years[22]. Figure 3 illustrates the region under analysis. No district from the coast or the jungle is included. The design allowed the inclusion of districts from the north, central and south highlands. I preset the color ranges based on distance to provide an idea of the district's proximity to mines, but I consider districts as treated whenever it had a mine within the 100km range or below.

[20]The *Andes* mountains divide the country into two parts, the coast on the West and the rain-forest on the East, leaving the *Andes* as a middle region. This partition influences mainly transport costs, which ultimately explains the differences in productivity as documented by Sotelo (2015).

[21]Former Peruvian president Manuel Pardo, during the early days of the Peruvian Republic in 1862, coined an illustration that has survived to this day: the freight cost from Jauja (a small city in the central highlands) to the capital, Lima was four times higher than the maritime freight from the capital harbor, Callao, to Liverpool. See Pardo (1996)

[22]As noted before, 41 of the original *control* districts were influenced by the opening of new mines. I removed these districts.

Figure 3: Mining and Non-Mining Districts



Notes: [1] Red coluring intensifies with proximity to any of the 27 mines operating in 1993. Light red represents the districts not affected by mining activity (within 101km and 200km). [2] Grey area represents districts that are not considered in the analysis.

The proximity to the mine is not the only difference between districts. The empirical strategy actually exploits the fact that mines had different portfolios of minerals in order to construct a measure of the price boom experienced by each mining districts. I do this in two stages. First, I estimate the weighted average price change (from 1993 to 2007) for every mine:

$$\Delta P_g = \sum_m \kappa_m \Delta P_m \tag{2}$$

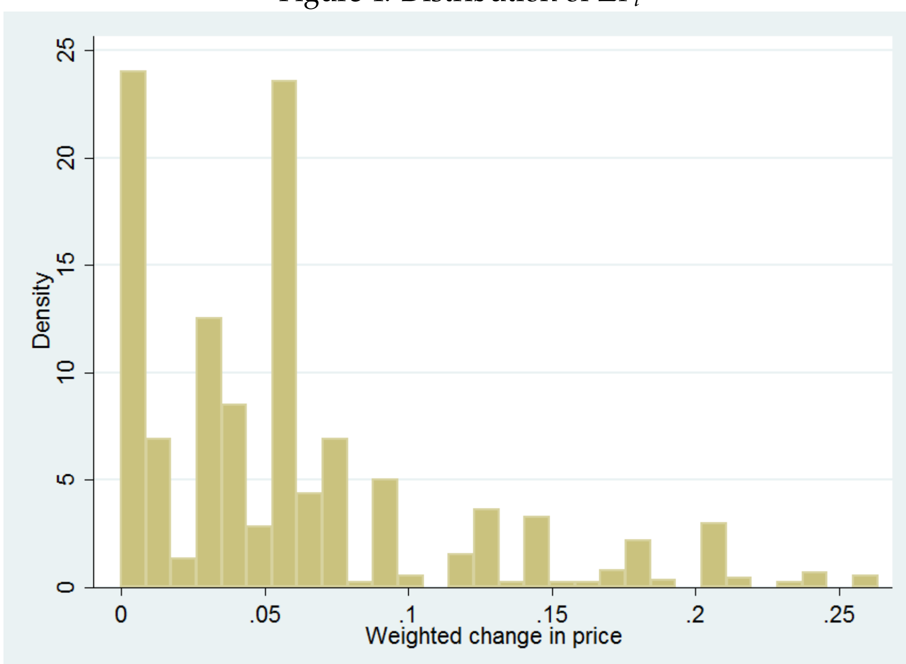
Where m={gold, silver, copper, zinc, lead}. κ_m is the mineral weight, estimated as the mineral production in 1994 valued at 1994 international prices. ΔP_m is the international price change (increase in percentage points) in the mineral from 1993 to 2007. g index each of the 27 mines. This measure exploits variability in the mineral portfolio of each mine.

In the second stage, I match every district in 1993 to all the mines that fell within the 100km distance threshold. Some districts were under the influence of many mines, therefore, the final measure of price boom adds one additional source of variation: the number of mines influencing the district. In concrete, the district measure that I construct is:

$$\Delta P_i = \sum_g \Delta P_{ig} \tag{3}$$

Where each district i was under the influence of G_i mines, each with a mineral portfolio that yielded a price change ΔP_g. The measure ΔP_i is simply the sum of price changes over all mines that influenced the district. With this measure, districts surrounded by several mines will experience heavier influence of mining than districts close to one mine. Figure 4 plots the distribution of ΔP_i.

Figure 4: Distribution of ΔP_i



The empirical equation, therefore, for the effect on labor N in district i is:

$$\Delta\left(N_i\right) = \alpha + \beta \Delta P_i + \theta_k \Gamma_{ki} + \eta_p + \varepsilon_{it} \tag{4}$$

Where $\Delta(N_i) = \ln(N_{i2007}) - \ln(N_{i1993})$, which is the percentage change in employment in district i. I subsequently evaluate the effect by industry and skill group[23]. However, I also evaluate a different version: $\Delta(N_i) = (N_{i2007}/Pop_{i2007}) - (N_{i1993}/Pop_{i1993})$, which is the

[23] I define skilled worker if he or she has at least technical education. This information is available in the census and survey data. With this definition, 18% of the individuals in the survey data are high skilled. The census data indicates that 14% of the population was high skilled in 1993, while this percentage increased to 20% in 2007.

change in the employment rate, where $Pop_{i,1993}$ is always the district adult population (16 years old or more). In consequence, empirically, the first definition evaluates differences in the growth rate of the number of workers, while the second evaluates the differences in the change in the employment rate. Again, I extend this estimation to the industry and skill groups.

Having the dependent variable as change in rates as a complement to the change in (log) number of workers is an attempt to understand the re-shuffling of employment in the context of a geographical model with constant population. Then, to directly understand how much of the hypothetical change is explained by new high skilled or low skilled workers, the employment rate is separated by the share explained by those two categories. For instance, employment rate in the 1043 districts studied in 1993, was 51.9%. Out of this number, 4.4% was skilled employment, while 47.5% was low skilled employment. The average change in log number of employed people between 2007 and 1993 was -0.035 log points. The high skilled employment changed on average by 0.037 log points, while low skilled employment changed on average by -0.074 log points. In consequence, in this context, finding a positive effect on overall, high skilled and low skilled employment would be interpreted as overall and high skilled employment growing faster, while low skilled employment decreasing slower for those districts under the influence of large-scale mining activity.

The coefficient of interest is β which captures the effect of the boom in mineral prices on the city, as described above. θ_k is a vector with district controls: altitude, the historical coefficient of variation of rainfall, distance to Lima, land extension of the district and the initial level of population (in logs). η_p are province fixed effects. ε_{it} is the empirical disturbance.

The measure of wages corresponds to all individual earnings from main and secondary occupation expressed on a monthly basis at 2007 prices. All individuals with a dependent job or self-employed were considered. The analysis excludes individuals who report working as unpaid workers. From ENAHO I can also include several individual characteristics as controls. To measure the effect of the boom in mineral prices on wages I try three specifications. The first is simply an application of equation (4) at the individual level, which yields the following estimating equation:

$$\ln w_{cit} = \alpha + \beta \Delta P_i + \Omega_a \Pi_{act} + \theta_k \mathit{\Gamma}_{ki} + \eta_p + t_t + \varepsilon_{cit} \tag{5}$$

Where $\ln w_{cit}$ is the natural log of monthly wage of individual c living and working in district i at time t. The right hand side of the equation is similar to the employment equation, with the exception that I also control for a set of a individual characteristics Π_{act}: gender (male), age and its square, the number of years of schooling, household size, number of income earners in the household, dummies for water and electricity in the household, fixed effects for industry (two digits ISIC), job type (owner, self-employed, white collar, blue collar), year, t_t, and province, η_p. The variable ΔP_i is the same across time for each district and measures, as usual, the effect of the price change from 1993 to 2007.

The previous equation, however, does not exploit annual variation in the cross section. It does not control for district fixed effects either. To address this, I re-define the mineral price variable as a price index (base 1994) that uses as weights the mineral production of 1994, and is evaluated lagged one period to allow for adjustment: PI_{t-1}[24]. The empirical equation, in this case, take the following form:

$$\ln w_{cit} = \alpha + \beta PI_{it-1} + \Omega_a \Pi_{act} + \eta_i + t_t + \varepsilon_{cit} \tag{6}$$

The specification keeps the individual controls, but now geographical fixed effects are at the district level: η_i. Therefore, any change on wages steams from the time variation in the mineral price index.

4 Results

4.1 Employment, population and unemployment

Table 1 presents the baseline results for equation 4. Panel a. shows the results for the dependent variables as change in log levels, while panel b. evaluates the model with the dependent variable as change in the employment rate. There are statistically significant results for the variables measured as rates, in panel b. The columns on employment (4, 5 and 6) indicate that the increase in mineral prices resulted in higher change in employment rate for the districts under the influence of the mining activity. In particular, in column 4, a one standard deviation of the change of the price index (0.31) is related to a 4% (0.31x0.13) faster change in employment rate for those districts close to any mining activity. This means that, for instance, if both groups of districts experienced an increase in the employment rate, the increase in the mining districts was 4% higher for every standard deviation increase in the portfolio of mineral prices. This effect is large compared to the average change in the employment rate experienced in the sample of districts for the 1993-2007 period. On average, the change in total employment rate was -3%. The result found here suggests that the boom in the mining activity offset the decline in the average employment rate experienced in the sample districts and instead, employment grew by 1%.

Columns 5 and 6 account for employment change by skill type. By doing this, the coefficient for total employment can be broken into the two skill categories. Column 5 indicates that out of the 0.13 percentage points effect, 0.05 is explained by increase in high skilled employment rate, while the remaining 0.07, by low skilled employment (column 6). The three results are statistically significant at 1%.

Regarding population, columns 2 and 3 in panel b, however, indicate that there was a reshuffling in the composition of the population by skill. The estimated coefficient for the change in the share of high skilled population is 5%, which suggests that for every additional

[24] That is, the weighted mineral price average for every year.

Table 1: Change in Employment: 2007-1993

	Population			Employment			Unemployment		
	Ln. N.	High Skilled	Low Skilled	Rate	High Skilled	Low Skilled	Rate	High Skilled	Low Skilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
a. Changes in Log Numbers									
ΔP	-0.09	0.10	-0.15	0.12	0.31	0.05	-0.44***	-0.53	-0.47***
	(0.14)	(0.25)	(0.13)	(0.17)	(0.21)	(0.16)	(0.12)	(0.36)	(0.11)
R^2	0.41	0.37	0.47	0.31	0.36	0.30	0.42	0.34	0.45
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124
b. Changes in Shares									
ΔP		0.05**	-0.05**	0.13***	0.05***	0.07***	-0.13***	-0.00	-0.13***
		(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.04)
R^2		0.52	0.52	0.33	0.52	0.25	0.33	0.37	0.36
Observations		1043	1043	1043	1043	1043	1043	1043	1043
Clusters		124	124	124	124	124	124	124	124

Notes: [1] Data source: population censuses of 1993 and 2007. [2] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample), the log of district population in 1993 and province fixed effects. [3] Panel a. measures the dependent variales in log changes, whereas panel b uses the change in rate. For the estimation of rates the denominator is always the district adult population (16 years old or more). [4] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

standard deviation of the mineral prices, the share of high skilled individuals increased by 1.6%. This result is not small. The average percentage of high skilled people in both periods was 7.3%, while the average change in the share of high skilled individuals was 3.7%. The estimated effect indicates, therefore, that for every standard deviation increase in the mineral prices, mining districts experienced an additional increase that was 43% (0.016 out of 0.037) higher than the average increase in in the share of high skilled population.

Panel a offers no statistically significant result either for population or employment, however the sign of the estimated coefficients are in line with the results in panel b. Which suggests that more than in absolute terms, mining had an effect on the structure of the labor market.

Columns 7, 8 and 9 evaluate any impact on unemployment. Total unemployment decreased in districts close to the mining activity measured both as the change in log number of unemployed individuals (panel a) or as a share (panel b). The reduction of unemployment is particularly evident for low skilled workers. From panel a, mining districts experienced a faster decline in growth rate of the number of unemployed individuals by a magnitude of 14% (0.47x0.31) by every standard deviation in the mineral price index. As a share (panel b), mining districts saw low skilled unemployment rate decline by 4% (0.13x0.31) faster than in non-mining districts.

Results hitherto suggest that the mining boom experienced from 1993 to 2007 had effects on the employment rate of the local economy. This increase in employment reached both skilled and unskilled workers, with a certain emphasis on skilled workers. The proportion of skilled individuals also increased in the local economy close to the mine, while unemployment for the low skilled group dropped. Employment results in columns 5 and 6 of panel b are in line with the theoretical predictions under the assumption that skilled workers are more mobile than unskilled workers.

Table 2 evaluates the heterogeneous effect on employment by industries. Panel (a) evaluates the effect on the growth rate of employment (difference in logs), and indicates that employment in the mining sector grew faster. The effect on this sector is quite large. The average increase in mining employment in the districts included in the sample between 1994 and 2007 period was 84%. The coefficient for the effect on overall mining employment reported in column 1, 0.89, indicates that by every standard deviation increase in the price of minerals (0.31), the mining districts experienced an additional increase in employment of 28% (0.89x0.31). This effect was stronger for skilled employment. The average increase in skilled employment between 1993 and 2007 was 61%. The estimated coefficient for the effect on skilled employment was 1.00, which interpreted in terms of standard deviations reports an extra increase in skilled employment of 31% (1.00x0.31) in the mining districts. The rest of the coefficients in panel (a) are not statistically significant.

Table 2: Change in Employment: 2007-1993, By Industry and Skill

	Mining			Tradable			Non-Tradable			Agriculture		
	N	H	L	N	H	L	N	H	L	N	H	L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
a. Changes in Log Numbers												
ΔP	0.89*	1.00***	0.70	0.08	-0.12	0.04	-0.01	0.20	-0.17	0.08	-0.02	0.06
	(0.48)	(0.37)	(0.45)	(0.20)	(0.24)	(0.19)	(0.22)	(0.23)	(0.22)	(0.17)	(0.27)	(0.16)
R^2	0.29	0.31	0.29	0.26	0.18	0.26	0.30	0.29	0.29	0.27	0.27	0.27
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
b. Changes in Shares												
ΔP	0.05**	0.03***	0.01	-0.00	-0.00	-0.00	0.01	0.01	0.00	0.06**	0.01	0.05**
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.18	0.23	0.15	0.21	0.27	0.22	0.33	0.49	0.22	0.29	0.48	0.28
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124

Notes: [1] Data source: population censuses of 1993 and 2007. [2] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample), the log of district population in 1993 and province fixed effects. [3] Panel a. measures the dependent variales in log changes, whereas panel b uses the change in rate. For the estimation of rates the denominator is always the district adult population (16 years old or more). N holds for total, H for high skilled workers and L for low skilled workers. [4] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

Panel (b) reports the changes in the employment rate. The estimated coefficients are consistent with the idea of the mining boom increasing the employment rate across sectors. To understand these coefficients it is worth recalling the way they are defined. Each employment category (industry, or industry-skill type) is represented as a share of total employment. In consequence, the total effect on employment reported in table 1 (0.13; panel (b) column 4) is divided between the four sectors considered in the analysis. In that regard, the results show that 84.6% of that effect was driven by increase in the employment share in mining (0.05, column 1) and agriculture (0.06, column 10). More interestingly, out of the 0.05 percentage points effect in the mining employment, 0.03 are explained by and increase in the high skilled employment. Whereas in the agriculture sector, out of the 0.06 percentage points increase, 0.05 is explained by low skilled employment. This result, therefore, confirms the heterogeneous nature of the effect of the boom in mineral prices at both levels: sectors and skills.

The no effect on tradable and non-tradable industries is in itself an interesting result. The idea that the tradable sector may be particularly hurt by a boom in an industry that increases the costs of factors but not the price of the traded goods finds no validation in the current set of results.

In order to confirm the validity of the results, tables 3 and 4 conduct a falsification test. In table 3 I evaluate whether the population composition and employment measured as rates before the boom in mineral prices were affected by future boom. Panel (a) of table 3 evaluates the population and employment variables as in 1993 (all variables measured as rates except for column 1 which reports the log number of population and column 4 which reports results for the change in log employment). There is no result statistically significant in panel (a): the spatial difference between mining and non-mining districts was not statistically significant. Panel (b) proceeds with the same evaluation, but using the change from 1981 to 1993 in the dependent variables. For this evaluation, however as explained above, I can only use 22 regions, which reduces the number of districts to 931. Results are reassuring, and the future mining boom is not associated with previous trends in population or employment, except for the employment rate which is negatively associated with the future mining boom. However, if only non-mining employment is considered, the placebo test provides the expected result. At this point results at least are reassuring for all variables but those related directly to the mining. It is also possible that the missing information from the 112 missing districts would validate the placebo test. I will leave this to future research.

Table 4 directly explores whether the boom in mineral prices between 1993-2007 explained the change in the employment rate by industry and skill group from 1981 to 1993. Again, it is not the case, although the estimations include only 931 districts.

Table 3: Balance: Demographics in 1993

	Population			Employment				Non-Mining Employment		
	Ln. N.	High Skilled	Low Skilled	Ln. N.	Rate	High Skilled	Low Skilled	Rate	High Skilled	Low Skilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
a. Dependent variables in shares in 1993										
ΔP	-0.30	0.01	-0.01	-0.41	-0.07*	-0.00	-0.07	-0.08*	-0.01	-0.07
	(0.68)	(0.04)	(0.04)	(0.65)	(0.04)	(0.02)	(0.06)	(0.04)	(0.02)	(0.06)
R^2	0.54	0.36	0.36	0.53	0.31	0.31	0.31	0.32	0.29	0.32
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124
b. Dependent variables change in shares 1993-1981										
ΔP	0.02	0.01	-0.01	-0.11	-0.09**	-0.00	-0.08**	-0.04	-0.00	-0.04
	(0.21)	(0.01)	(0.01)	(0.25)	(0.04)	(0.01)	(0.04)	(0.04)	(0.01)	(0.04)
R^2	0.38	0.46	0.46	0.32	0.20	0.45	0.17	0.20	0.46	0.17
Observations	931	931	931	931	931	931	931	931	931	931
Clusters	112	112	112	112	112	112	112	112	112	112

Notes: [1] Data source: (i) population census of 1993 for panel a. (ii) population censuses of 1993 and 1981 for panel b. [2] 1981 census has fewer districts because, according to the public information provided by INEI, it was not possible to recover data from three regions (Apurimac, Loreto and San Martin). Population of these three regions represent 6 % of total population in 1981. Moreover Loreto region, and partially San Martin, fall outside the sample of districts used in this analysis. see INEI (2015). [3] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample) and province fixed effects. [4] Column 1 is the natural log of district population (above 16 years old). Columns 2 and 3 are the share of high skilled and low skilled individuals. Columns 4 to 7 refer to employment. Column 4 is the natural log of the number of workers in the district, column 5 is the employment rate, columns 6 and 7 are the number of high and low skilled workers ove the population. Columns 8-9 replicate exclude mining workers. [5] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

Table 4: Balance: Pre-Trends in log level employment: 1993-1981

	Tradable			Non-Tradable			Agriculture		
	N	H	L	N	H	L	N	H	L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔP	0.00	0.00	0.00	-0.02	-0.00	-0.01	-0.03	0.00	-0.03
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.04)	(0.00)	(0.04)
R^2	0.22	0.34	0.21	0.20	0.44	0.20	0.16	0.27	0.16
Observations	931	931	931	931	931	931	931	931	931
Clusters	112	112	112	112	112	112	112	112	112

Notes: [1] Data source: population censuses of 1993 and 1981. [2] 1981 census has fewer districts because, according to the public information provided by INEI, it was not possible to recover data from three regions (Apurimac, Loreto and San Martin). Population of these three regions represent 6 % of total population in 1981. Moreover Loreto region, and partially San Martin, fall outside the sample of districts used in this analysis. see INEI (2015). [3] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample) and province fixed effects. [4] All dependent variables are the change in the employment rate of the industry, by skill type. In all cases, the denominator is the total population whle the numerator is the number of workers in the corresponding industry and industry-skill pair. N holds for total, H for high skilled workers and L for low skilled workers. [5] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

I tested the same variables using the the log number of individuals instead, and results were even more reassuring since I found no effect at all in the placebo test. For space considerations I did not report the tables.

4.2 Effect on wages

Results so far indicate that high skilled workers found more jobs in districts under the influence of the mineral price boom. This also meant that the share of individuals with high skill increased while the proportion of low skilled individuals decreased. The theoretical framework predicts that under this circumstance the wage for low skilled workers should experience a higher increase than the wage for high skilled workers.

Table 5 presents the results of estimating equations (5) in panel a., and equation (6) in panel b. The interpretation of these equations are slightly different than the employment estimations. In this case, the boom of mineral prices explains wage differentials in the log levels of the two groups of districts, rather than the growth differences.

Table 5: Wages by Skill: 1997-2007

	Both	High Skilled			Low Skilled		
		>= Uni.	>= Tec.	>= Sec.	< Uni.	< Tec.	< Sec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. ΔP							
ΔP	0.17***	0.03	0.16*	0.13***	0.19***	0.19***	0.22***
	(0.04)	(0.09)	(0.09)	(0.05)	(0.04)	(0.05)	(0.06)
R^2	0.51	0.48	0.46	0.46	0.47	0.44	0.39
Observations	73272	7467	14511	27750	65791	58747	45508
Clusters	702	381	508	648	702	702	702
b. PIt							
PI_{it-1}	0.38*	-0.01	-0.15	-0.22	0.42**	0.53**	0.72***
	(0.20)	(0.47)	(0.31)	(0.22)	(0.21)	(0.22)	(0.24)
R^2	0.53	0.50	0.48	0.48	0.49	0.46	0.42
Observations	73272	7467	14511	27750	65791	58747	45508
Clusters	702	381	508	648	702	702	702
c. Production							
$Production_{it-1}$	0.11***	0.13**	0.07**	0.13***	0.10***	0.11***	0.08**
	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.53	0.50	0.48	0.48	0.49	0.46	0.42
Observations	73272	7467	14511	27750	65791	58747	45508
Clusters	702	381	508	648	702	702	702

Notes: [1] Data source: ENAHO 1997-2007. [2] Dependent variable is the log of monthly wage of main and secondary ocupation at 2007 prices. Column 1 considers all individuals. Columns 2, 3 and 4 use data from high skilled workers. High skilled are those individuals with university education (column 2), or at leat technical education (column 3), or at least secondary education (column 4). Columns 5, 6 and 7 refer to low skilled wages as the alternative to columns 1, 2 and 4, respectively. [3] Panel a. replicates the empirical equation used in the district level regression. Panel b. estimates the effect on wages using a yearly commodity price index. Panel c. uses annual mining production. Individual controls included in panels b. and c.: gender (male), age and its square, the number of years of schooling, household size, number of income earners in the household, dummies for water and electricity in the household, fixed effects for industry (two digits ISIC), job type (owner, self-employed, white collar, blue collar), year and district. [4] Errors clustered at province level in panel a. Errors clustered at district level in panels b. and c. Coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

I use 1997-2007 for the estimation. The government started producing ENAHO since that year, therefore I cannot collect individual wage information for years before 1997.

Column 1 estimates the effect on total monthly wage, and finds a positive effect in all specifications. The coefficient shown panel (a), 0.17, suggests that every standard deviation increase in the mineral prices was associated with an average wage 5.2% (0.17x0.31) higher in the mining districts. Panel (b) estimates the equation controlling for district and year fixed effects, and uses an annual price index, instead. The effect of a one standard deviation increase in this case is higher: mining districts reported a monthly wage 11.8% higher (0.38x0.31[25]). Using annual production, as in panel (c), the estimated coefficient is 0.11, which represents a wage 8.6% (0.11x0.78[26]) higher in mining districts. The estimates of panel (c), however, may be less defensible in terms of endogeneity. Annual mineral production depends on the amount of labor and capital available every year and attracted to the local economy. In that regard, results from panels (a) and (b), are more reliable: they use 1994 production as weight for the index. Panel (a) uses the 1994-2007 change in prices, while in panel (b) the estimation uses an index constructed with 1993-1994 productivity weights.

Columns 3 and 6 show the estimated effect of the mineral price boom on the monthly wage by the skill type. As predicted by the theory, the wage for low skilled workers should experience a higher increase than the wage for high skilled workers. This is reflected in column 6, panel (a), using the baseline definition of high skill: technical studies[27]. The estimated coefficient is 0.19, which is 3 percentage points higher than the estimated effect for high skilled wage (0.16 in column 3). However these two coefficients are not statistically different.

How does the skill threshold affects the estimates? A more strict definition of high skill, university degree[28], makes the result clearer, and this is reflected in columns 2 for high skilled wage and 5 for low skilled wage. With this definition, the effect on low skilled wages is the only one statistically different from zero, which ultimately implies that this type of workers are the only wage gainers from the productivity shock in the natural resource sector.

With a less strict threshold for skill (secondary education), the estimated effects are again not statistically different (although the higher point estimate for low skilled wage): the estimated effect for low skilled wage is 0.22, with an standard error of 0.06, while the estimated effect for high skilled wage is 0.13 with an standard error of 0.05.

The estimation procedure that consider the annual price index, reported in panel (b), does indicate that low skilled wages reacted positively in mining districts, while high skilled wages did not. More interestingly, the point estimate for the effect on low skilled wage increases for lower thresholds in the skill definition. In concrete, for the lowest threshold that considers an individual as low skilled if his or her qualification is smaller than secondary (that is, individuals with primary education and no education) yields an estimated effect of 0.72. This effect suggests that low skilled workers in mining districts had a wage 22% (0.72x0.31) higher than

[25]Mean and standard deviation of the annual index for mineral prices: 0.29 and 0.31, respectively

[26]Mean and standard deviation of annual production: 0.79 and 0.78, respectively

[27]I assumed technical studies as the threshold for skilled labor. But I evaluate the sensitivity of this threshold later in this section.

[28]With this definition, 9% of the individuals in the survey sample are high skilled.

the wage of low skilled workers in non-mining districts.

Estimates from panel (c) show estimated coefficients for both skill groups that are not statistically different from each other.

Results on wages so far do not clearly reflect a difference response by skill type. It is only on panel (b) that low skilled wages reacted positively to the boom in mineral prices. In table 6 I shed more light on the heterogeneous wage response by industry. The estimation procedure is the same, but in this case I constrain the sample of individuals depending on the industry the belong into. Panel (a) suggests that there is only a detectable effect on the monthly wage of agricultural workers. Surprisingly, there is no effect on the wage of mining workers, but this may be a consequence of the reduced number of individuals working in the mining sector in the 10 years period from 1997 to 2007 included in the sample: 1,686. The estimated coefficient reported in column 4, 0.25, suggests that the average monthly wage of agricultural workers in mining districts was 7.8% higher that the average monthly wage of agricultural workers in non-mining districts by every standard deviation increase in the price index for minerals. The effect on agriculture found in panel (a) can be explained by the large share of low skilled workers in that sector. Only 3% of the individuals in the agricultural sector have at least technical education, whereas 73% have no education or primary education.

Table 6: Wages by Industry: 1997-2007

	Mining	Tradable	Non-Tradable	Agriculture
	(1)	(2)	(3)	(4)
a. ΔP				
ΔP	-0.27	-0.06	0.03	0.25***
	(0.23)	(0.13)	(0.06)	(0.08)
R^2	0.67	0.61	0.44	0.29
Observations	1686	6402	34458	30726
Clusters	187	516	672	696
b. PIt				
PI_{it-1}	0.25	0.70	0.00	0.47
	(0.64)	(0.54)	(0.18)	(0.32)
R^2	0.73	0.65	0.46	0.33
Observations	1686	6402	34458	30726
Clusters	187	516	672	696

Notes: [1] Data source: ENAHO 1997-2007. [2] Dependent variable is the log of monthly wage of main and secondary ocupation at 2007 prices, by indistry type. [3] Panel a. replicates the empirical equation used in the district level regression. Panel b. estimates the effect on wages using a yearly commodity price index. Individual controls included in panel b. : gender (male), age and its square, the number of years of schooling, household size, number of income earners in the household, dummies for water and electricity in the household, fixed effects for industry (two digits ISIC), job type (owner, self-employed, white collar, blue collar), year and district. [4] Errors clustered at province level in panel a. Errors clustered at district level in panel b. Coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

Panel (b) finds a positive effect for mining, tradable and agriculture, but none of the coefficients is statistically significant. Panel (c), which shows the results for an estimation that uses annual production, suggests that the wages in the mining, tradable and agricultural sectors were higher in mining districts. However, this estimation is less reliable due to potential problems of endogeneity.

4.3 Effect on migration

So far the results focused on employment and wages. The estimated effects are in line with the theoretical predictions of higher employment, with an emphasis on high skilled workers, and therefore a higher increase in low skilled wages. In this section I address the explanation of the results from the migration perspective. However, I adopt a descriptive point of view here.

As mentioned in equation 1, the current population, or labor force can be categorized in four groups, indexed by m: *locals*, *new locals*, *individuals who returned*, and *new comers*. To investigate the effect of the mining boom in any of these categories, I estimate the following equation:

$$\Delta\left(M_{mi}\right) = \alpha + \beta \Delta P_i + \theta_k \mathit{\Gamma}_{ki} + \eta_p + \varepsilon_{it} \tag{7}$$

This equation is the same as (4) but uses any of the migration categories as dependent variable. Again, as in the case of population and employment, I measure the effect of the mining boom over two different types of dependent variables. First, $\Delta\left(M_{mi}\right) = \ln M_{mi,2007} - \ln M_{mi,1993}$ represents the log change in the number of migrants in category m in district i[29]. Second, I also measure the effect of the mining boom over $\Delta\left(M_{mi}\right) = M_{mi,2007}/Pop_{i,2007} - M_{mi,1993}/Pop_{i,1993}$, which in this case is defined as a share of the working population[30].

Table 7 shows the results. Panel (a) presents the results using the change in the log number of individuals for population (panel a.1) and labor force (panel a.2), while panel (b) groups the results for the migration rates measured as population share (panel b.1) of employment share (panel b.2)[31].

[29] Later also considered by industry and skill group.
[30] Individuals 16 years old or more
[31] For example, when measuring the proportion of locals in panel b.1 I use the total number of locals (employed or not) over the working population; while in panel b.1 I use only the locals who are employed in the numerator, leaving the denominator the same.

Table 7: Change in Migration Composition: 2007-1993

	N22			N21			N12			N11		
	Locals			Returned			New Locals			New Comers		
	N	H	L	N	H	L	N	H	L	N	H	L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						a. Changes in Log Numbers						
a.1 Population												
ΔP	-0.11	-0.04	-0.17	0.02	-0.03	-0.00	-0.00	0.22	0.02	0.30	0.45	0.27
	(0.12)	(0.23)	(0.11)	(0.17)	(0.17)	(0.18)	(0.14)	(0.21)	(0.13)	(0.29)	(0.33)	(0.27)
R^2	0.77	0.44	0.78	0.41	0.25	0.39	0.44	0.29	0.44	0.34	0.28	0.33
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
a.2 Employment												
ΔP	0.09	0.25	0.02	0.20	0.01	0.27	0.09	0.39*	0.08	0.33	0.37	0.39
	(0.14)	(0.19)	(0.13)	(0.14)	(0.14)	(0.17)	(0.18)	(0.21)	(0.16)	(0.27)	(0.29)	(0.26)
R^2	0.62	0.37	0.61	0.37	0.24	0.35	0.36	0.27	0.34	0.32	0.31	0.29
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
						b. Changes in Shares						
b.1 Population												
ΔP	-0.00	0.03	-0.04	-0.01	-0.00	-0.01	-0.01	0.01	-0.02	0.02	0.02*	0.01
	(0.02)	(0.02)	(0.03)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.47	0.50	0.50	0.32	0.20	0.34	0.15	0.37	0.15	0.72	0.26	0.79
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
b.2 Employment												
ΔP	0.09***	0.03***	0.06**	0.00	-0.00	0.00	-0.00	0.01**	-0.01	0.02*	0.01**	0.01
	(0.03)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.34	0.50	0.30	0.31	0.17	0.34	0.20	0.45	0.17	0.49	0.31	0.56
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124

Notes: [1] Data source: population censuses of 1993 and 2007. [2] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample), the log of district population in 1993 and province fixed effects. [3] The dependent variables are the current population composition (share) of the district according to migration categories. *Locals* are those individuals born in the district that were living there five years ago. *Returned* are individuals born in the district who were not living there five years ago. *New Locals* are individuals not born in the district but were living there five years ago. *New Comers* are individuals who were not neither born or residents of the districts five years ago. For each category N holds for total, H for high skilled workers and L for low skilled workers. [4] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

Focusing on panel a.2, which presents the results for the the change in log employment, there is only a 10% significant increase for the log number of high skilled *new locals* for mining districts (column 8). In population terms, the number of low skilled locals (column 3, panel a.1) seems to decline, but this result is not statistically significant.

Panel b evaluates the changes in each migration category as share of population and employment. There is no discernible difference across migration categories to explain the reshuffle of population (panel b.1). However, in terms of employment (panel b.2), the effect over the proportion of locals is 0.09 percentage points (column 1). This coefficient bear an important result. In table 1 the estimated effect of employment was 0.13, therefore, the coefficient 0.09 estimated here indicates that 0.09 out of the 0.13 points increase in employment is explained by more employment of locals, this represents 69%. Column 10 in panel b.2 reports a coefficient of 0.02 which bears similar interpretation: 0.02 percentage points out of the 0.13 percentage points effect found in the baseline results are explained by new comers, which represents 15% of the total effect on employment following the boom in mineral prices. This of course, remains a descriptive result, but is telling in the sense that most of the effect on employment is driven by an increase in the employment of locals.

Which locals? Columns 2 and 3 in panel b.2 allow further analysis. Out of the 0.09 percentage points effect on the employment of locals is filled by low skilled locals: the estimated coefficient for this category is 0.06 percentage points. High skilled locals also benefit: the estimated coefficient is 0.03. To put this into perspective it is worth looking at the average changes in the migration rates. The average change in the migration rate of locals between 1993 and 2007 was -0.01 percentage points: the proportion of employed locals experienced a reduction in general. The estimated coefficient of 0.09 signals a large effect on the share of employed locals. By skill categories, the estimated effects are also important. The average change in the share of employed locals with high skill was 0.02 percentage points, which is not too small compared to the estimated effect for mining districts: 0.03. The effect on low skilled locals is the largest when compared to the average change. From 1993 to 2007 the proportion of low skilled locals employed fell by 0.04 percentage points, while mining districts following the boom experienced a positive effect, 0.06.

The effect on new comers can be dissected in a similar fashion. The average change in the proportion of new comers employed from 1993 to 2007 was -0.01. The change for high skilled was 0.004 while for low skilled, -0.02, the estimated effects for the total proportion of employed new comers was 0.02, 0.01 for high skilled and 0.01 for low skilled (although this is not statistically significant). Results, therefore, indicate an important effect in the composition of the employment by migration category, with the proportion of locals benefiting more from the boom in mineral prices.

How does this result look between industries? Table 8 shows this in detail for the change in the log number of people employed in the district. The first three columns show a clear effect on the growth of locals employed in the mining sector in the district after the increase in the mineral prices. The coefficient estimated in column 1, 0.96, suggests that mining districts experienced a growth in the number of employed locals in the mining sector that was 29.8% (0.96x0.31) higher than in non-mining districts for every standard deviation increase in the index of mineral prices. Such effect is slightly higher for high skilled workers, where the estimated coefficient is 1.02. The coefficient for low skilled locals employed in the mining sector is 0.70. Interestingly, the mining boom also attracted high skilled individuals who were born in the district and returned from somewhere else. This result is shown in column 5, with a coefficient of 0.33. Something similar can be interpreted for high skilled *new locals* (individuals not born in the district but who were living there since five years ago) with an estimated coefficient of 0.54 (column 8).

Table 8: Change in Migration Composition by Industry - Log Levels

	N22			N21			N12			N11		
	Locals			Returned			New Locals			New Comers		
	N	H	L	N	H	L	N	H	L	N	H	L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
a. Mining												
ΔP	0.96***	1.02***	0.70**	0.30	0.33***	0.14	0.57*	0.54***	0.44	0.55	0.29	0.50
	(0.34)	(0.22)	(0.35)	(0.18)	(0.08)	(0.23)	(0.30)	(0.17)	(0.31)	(0.41)	(0.37)	(0.38)
R^2	0.35	0.39	0.33	0.27	0.28	0.22	0.23	0.28	0.19	0.24	0.27	0.22
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
b. Tradable												
ΔP	0.13	-0.14	0.08	-0.22*	-0.12	-0.22*	-0.38	-0.11	-0.31	0.05	0.10	-0.07
	(0.22)	(0.30)	(0.19)	(0.12)	(0.11)	(0.13)	(0.26)	(0.19)	(0.28)	(0.22)	(0.15)	(0.21)
R^2	0.28	0.24	0.28	0.22	0.21	0.21	0.22	0.21	0.22	0.22	0.18	0.22
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
c. Non-Tradable												
ΔP	-0.07	0.17	-0.18	-0.18	-0.18	-0.08	-0.09	0.33	-0.14	0.09	0.18	0.16
	(0.22)	(0.28)	(0.19)	(0.17)	(0.17)	(0.20)	(0.19)	(0.24)	(0.16)	(0.26)	(0.28)	(0.27)
R^2	0.43	0.32	0.39	0.27	0.24	0.24	0.32	0.24	0.28	0.30	0.30	0.23
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
d. Agriculture												
ΔP	0.05	0.06	0.04	0.45**	0.20	0.47**	0.36*	0.53***	0.33	0.37	0.37	0.34
	(0.15)	(0.25)	(0.14)	(0.18)	(0.18)	(0.18)	(0.21)	(0.17)	(0.22)	(0.24)	(0.29)	(0.23)
R^2	0.47	0.29	0.47	0.30	0.16	0.29	0.30	0.25	0.29	0.31	0.18	0.31
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124

Notes: [1] Data source: population censuses of 1993 and 2007. [2] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample), the log of district population in 1993 and province fixed effects. [3] The dependent variables are the current population composition (share) of the district according to migration categories, by industry as indicated in panels. *Locals* are those individuals born in the district that were living there five years ago. *Returned* are individuals born in the district who were not living there five years ago. *New Locals* are individuals not born in the district but were living there five years ago. *New Comers* are individuals who were not neither born or residents of the districts five years ago. For each category N holds for total, H for high skilled workers and L for low skilled workers. [4] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

There is no statistically significant result in the tradable or non-tradable sectors.

Panel (d) shows the results for the agriculture sector. There is a positive effect for individuals who returned and found a job in the agricultural sector, 0.45, which interestingly is focused in low skilled workers, 0.47. For every standard deviation increase in the index for mineral prices, the number of low skilled workers in the agricultural sector grew 14.6% (0.47x0.31) faster in mining districts. Interestingly, there is also an effect in the number of *new locals* who found a job in the agricultural sector: 0.36, which is focused in the group of high skilled workers, 0.53.

Table 9 re-evaluate these results in terms of employment shares. Recalling that the total effect on the employment rate was 0.13, the sum of all coefficients for the total estimates (columns 1, 4, 7 and 10) should add up to this number[32]. In that regard, this table is useful to understand the contribution of every sector to the total effect on employment. Column 1 in the set of estimates for the mining sector indicates that out of the 0.13 effect on total employment, 0.03 is explained by an increase in the employment of locals working in the mining sector, and 0.06 percentage points are explained by locals working in the agriculture sector. More interesting, all the effect on locals who work in the agricultural sector come from the low skilled category (column 3, panel d), whereas the increase in mining employment is mostly explained by high skilled locals. The rest of the coefficients are statistically insignificant or very close to zero. The later, again is a result in itself for the tradable and non-tradable sector. This results confirm if the tradable sector did not benefit from the mining boom it was not harmed either.

[32]Due to rounding it does not.

Table 9: Change in Migration Composition by Industry - Shares

	N22			N21			N12			N11		
	Locals			Returned			New Locals			New Comers		
	N	H	L	N	H	L	N	H	L	N	H	L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
a. Mining												
ΔP	0.03**	0.02**	0.01**	0.00**	0.00***	0.00*	-0.00	0.00***	-0.00	0.02	0.01	0.01*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.23	0.23	0.22	0.20	0.27	0.14	0.17	0.15	0.21	0.16	0.21	0.12
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
b. Tradable												
ΔP	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.26	0.29	0.26	0.18	0.08	0.20	0.14	0.20	0.16	0.10	0.14	0.10
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
c. Non-Tradable												
ΔP	0.00	0.01	-0.01	-0.00	-0.00	-0.00	-0.01	0.00	-0.01**	0.00	0.00	0.00
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
R^2	0.29	0.44	0.23	0.20	0.18	0.20	0.28	0.45	0.19	0.30	0.31	0.27
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124
d. Agriculture												
ΔP	0.06***	0.00	0.06***	0.01*	0.00	0.01**	0.01	0.00***	0.01	-0.00	0.00*	-0.00
	(0.02)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
R^2	0.30	0.49	0.29	0.34	0.08	0.34	0.21	0.28	0.21	0.70	0.16	0.71
Observations	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Clusters	124	124	124	124	124	124	124	124	124	124	124	124

Notes: [1] Data source: population censuses of 1993 and 2007. [2] All regressions include as controls: altitude, historical coefficient of variation of rainfall, distance to Lima (not included in the sample), the log of district population in 1993 and province fixed effects. [3] The dependent variables are the current population composition (share) of the district according to migration categories, by industry as indicated in panels. *Locals* are those individuals born in the district that were living there five years ago. *Returned* are individuals born in the district who were not living there five years ago. *New Locals* are individuals not born in the district but were living there five years ago. *New Comers* are individuals who were not neither born or residents of the districts five years ago. For each category N holds for total, H for high skilled workers and L for low skilled workers. [4] Errors clustered at province level, and coefficients that are statistically different from zero are denoted by the following system: *10%, **5% and ***1%

To summarize, results indicate that the mining boom exerted a positive influence over the employment share of the districts within 100km distance to any large scale mining project in 1993. Employment grew 13% faster, which can be read as 4% faster increase by every standard deviation increase (0.31) in the index of mineral prices at the local level. As a share, low skilled employment contributed with 7% while high skilled employment contributed with 5%. Unemployment declined by 13% and was focused on the group of low skilled workers. The growth in the employment rate was due to higher employment rates in the mining and agriculture sectors. No effect for tradable and non-tradable industries. The change in mining employment was mainly explained by higher high skilled employment while in the case of the agriculture industry, low skilled employment explained the increase.

In migration terms, most the increase in the employment share was explained by a higher share of employed locals. The majority of them, in turn, were low skilled, working in the agriculture sector. Higher high skilled employment in the mining sector was also filled by locals.

In the following section I discuss possible explanations for these results.

5 Discussion: are these results evidence of *Dutch Disease*?

Are these results together evidence of *Dutch Disease*? At this point it would be useful to recall the framework proposed by Corden and Neary (1982) to understand the existence of *Dutch Disease*. The results presented in this chapter support the hypothesis in favor of a *spending effect*.

In light of Corden and Neary (1982) this happens in the absence of a *resource movement effect*. The boom in the mining sector increases the marginal products of factors employed in the sector, which consequently draws resources out of the other sectors, which is followed by further adjustments in the economy. One of these adjustment takes place in the real exchange rate (prices of traded over non-traded goods).

Since the mining sector in reality draws very little resources from the rest of the economy (its labor absorption is very low while most of the capital used there is imported), the *resource movement effect* is negligible and the majority of its impact happens through the *spending effect*.

This is what the results show, the higher real income resulting from the boom leads to more spending on local services which consequently increase their prices and a real appreciation with more adjustments following. Notably, the agricultural sector, which is non-tradeable, benefits from the boom in the mining sector both in terms of employment and wages. Clearly this is evidence of the *spending effect* operating in the local economy.

Is this enough to conclude that local economies in Peru subjected to mining booms suffered a *Dutch Disease*? Certainly there are some of the elements in the results, mainly the increase in income, but the lack of evidence of de-industrialisation is also there. This lack of evidence of de-industrialisation however may be due to the lack of industrial activity in the region under analysis. Tradable employment in the region of analysis accounts for 9% of total tradable employment in the country. Even so, tradable employment in the area under analysis accounts for 6% of total employment in the same area. Nationally, the tradable sector accounts for 10% of total employment. Therefore the tradable sector in the highlands of Peru is very small, which may make difficult to detect any result pointing towards de-industrialisation.

Together these results suggest that there are some elements of the *Dutch Disease* (mainly a *spending effect*) among the results and the lack of evidence of de-industrialisation cannot be taken as clear cut evidence of no harm to the industrial sector because the industrial employment in the region under analysis is very low.

6 Conclusions

This chapter explored the effects of large-scale mining activity on local labor markets. It proposed a simple spatial framework that accounts for heterogeneous industries and workers. In its simple setting, the model predicts a larger labor response of high skilled workers for a given elasticity of substitution between high skilled and low skilled labor. As a consequence, their wage response is smaller than the wage response of the low skilled workers.

Using census data, I find that the employment rate grew faster in districts close to large-scale mining activity. Both, high skilled and low skilled employment rates grew, and the low skilled unemployment rate decreased.

The population size grew similarly in both types of districts, but there was a re-shuffle in the proportion of high and low skilled workers. The first increased in detriment of the second.

In terms of industries, the effect on employment focused on the mining and agriculture sectors. The increase in agriculture employment is explained by an increase in employment for low skilled workers. While for mining the effect is explained by high skilled labor. This is evidence of a *spending effect* in the light of the *Dutch Disease* framework since most of the agricultural sells locally.

Using individual data I find that wages increased with the mining boom, which again is evidence of a *spending effect*. The evidence is suggestive of an heterogeneous effect on the skill and industry, however it is not statistically different. By industry, agricultural workers gained the wage increase. The gain experienced by the agricultural workers may be explained by the large concentration of low skilled workers in this sector.

The chapter also explored the composition of population and employment according to the migration status of the individuals. Results indicate that most the effect on employment steam from higher employment for low skilled locals, mainly in agriculture.

As a concluding remark, this chapter sets the basic formulation to properly understand the geographical spillovers of industry booms in developing countries, however further extensions in the theoretical formulation should seek to endogenise the acquisition of education and the migration decision of individuals.

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