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ORIGINAL PAPER

Economic shocks and their effect on the schooling and labor participation of youth: evidence from the metal mining price boom in Chilean counties

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Abstract
We analyze the effect of an exogenous economic shock on youth, specifically their incentive for preferring to participate in the labor market over continuing their education. We examine the Chilean case and the sustained increase in the market price of the minerals extracted there during the period of Metal Mining Price Boom between the years 2003 and 2011. Chile is a large-scale producer of metals, being the world's largest producer of copper and the third largest producer of molybdenum. The prices of such metals increased steadily during the shock, what boosted the economic growth and the demand for labor. This shock altered the skill composition in the labor market, increasing the jobs for low- and medium–low-skilled workers in the counties more exposed to the shock, thus being the metal mining counties the most affected by its impact. According to this, our results show a negative impact of the shock on returns to schooling that simultaneously reduced school enrollment rates while increasing youth labor participation in those counties.

JEL Classification I26 · J24 · R11 · R23

1 Introduction

We aim to analyze how an exogenous economic shock, which presents a differentiated effect across the subnational units in a country, could impact on the schooling and labor force participation of youth, mainly in those territories more exposed to

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the shock. In this regard, the classic popular theory of human capital (Becker 1964) is a good guide to understanding the causal mechanism between an exogenous economic shock and the incentives for schooling. A shock that can temporarily alter the returns for schooling in the labor market could directly affect a young individual's decision to either join the labor market or continue their education (Willis and Rosen 1979; Zarkin 1983).

For this purpose, we examine the case of Chile between 2003 and 2011, experiencing that country a sustained increase in the market price of the minerals extracted there during this period. Chile is highly specialized in the extractive industry, being a large-scale producer of metals and the world's largest producer of copper and the third largest producer of molybdenum. Nevertheless, the mining activity is mainly concentrated in the northern regions, outstanding the case of Antofagasta where this activity represents approximately 50% of the GDP and 25% of the employment (OLAB 2016). Between 2003 and 2011, the commodity boom meant a sustained increase in the price of raw materials due to[1]: (i) the impact of investor flow driving through speculation (Singleton 2013) and (ii) the rapidly growing demand of emerging economies, i.e., China, which increased its imports of raw materials to sustain economic development (Radetzki et al. 2008). The positive shock on raw material demand resulted in higher prices and significant economic growth in Chile, mainly in mining areas.

The Chilean labor market was directly affected by the positive business cycle. During the price boom, Chile added approximately 1,000,000 new jobs,[2] growth that was concentrated in the mining sector, and particularly in the north of the country. Counties[3] specializing in mining saw rates of employment exceed the national average. However, the increase in employment there was primarily in low- or medium–low-skilled positions, most of which were either directly related to the mining sector or indirectly by the positive impact that this sector generated over the salaries, boosting the internal demand, for example, construction—which is also an important sector for creating the necessary infrastructure to the mining activity—as well as retail, trade and other services (Rehner and Vergara 2014). Additionally, the salary boom had an impact in terms of its distribution on the labor market between skilled and unskilled workers in the territories more exposed to the shock. Pellandra (2014) studied the effect of the metal mining price boom on the Chilean labor market and specifically those provinces with high indices of mining activity. Most of the benefits in terms of higher local wages accrued to less educated workers, while the increase in prices and exports (of raw materials) in those provinces had a more modest effect on the wages of college educated workers. Therefore, such gains

[1] As an example, the price of copper, which is the principal metal exported from Chile, went from nearly USD 0.80 per pound in 2003 to over USD 4.00 per pound in the second quarter of 2008. The price then stabilized between USD 3.00 and USD 4.00 through 2011.

[2] Data from the Chilean National Statistics Institute (INE) Labor Force Survey comparing the levels of employment between the years 2003 and 2011.

[3] In this paper, we will use the US term "county" as they have similar administrative features and size, comparable in some ways to comunas. Counties can contain typically several municipalities in much the way that some comunas do.

contributed to a larger reduction in skill premiums[4] in the most affected provinces (by the metal mining price boom) compared to others.

The aforementioned context makes Chile an interesting case. Some studies analyze the effects of exogenous economic shocks on the schooling within the context of an economic crisis at national level, but not considering the potential differences of the shock at a local level. Their results tend to be ambiguous; some studies show that a negative shock improves schooling enrollment as a result of the reduction of opportunity costs between education and work (Goldin 1999; Mckenzie 2003; Schady 2004). Other studies have found that when these shocks negatively affect household income, they result in youth preferring employment (Funkhouser 1999; Calero et al. 2009). This ambiguity is reflected in the work of Ferreira and Schady (2009), who found that the income level in each economy is important in understanding the increase/decline in schooling enrollment during a crisis. In rich countries they found that the lack of opportunities in the labor market for younger individuals encourages them to remain in education. In poorer economies there seems to prevail an income effect between schooling and joining the labor market, which produces a pro-cyclical pattern between schooling and growth. Thus, during times of crisis in countries where household income tends to decline, young people drop out of school in order to participate in the labor market and therefore minimize the shock's impact on the family budget.[5]

Much less is known on whether natural resource export booms have a negative effect on the schooling and working decisions of youth. Black et al. (2005) (hereafter BMS (2005)) carried out a leading study on the effects of the Appalachian coal boom on high school enrollment in Kentucky and Pennsylvania in the USA.[6] The coal boom increased the recruitment of workers in the mining sector and their salaries, most of whom possessed low educational levels. The shock reduced the value of education in the market and consequently discouraged high school enrollment. In their empirical analysis they found evidence that an increase of 10% in the salaries for low-skilled workers meant a decrease of approximately 5–7% in high school enrollment.

Despite the significant evidence found by BMS (2005), the authors did not assess whether the decrease in high school enrollment during the shock produced an increase in the labor force participation of youth. Therefore, although it is expected that the shock will encourage young people to drop out of school, there is no direct evidence on whether this shock produced a direct incentive for them to participate in the labor market, motivated by changes in returns to schooling. We aim to address

[4] The difference of the wages paid to high-skilled workers relative to wages paid to low-skilled workers.

[5] According to Ferreira and Schady (2009), 'declines in overall income levels raise the marginal utility of whatever the child can contribute to the family's budget today ([thus, having] an "antischooling" income effect) (p. 2).'

[6] Other studies analyze the impact of mining on consumption, poverty and inequality in local communities in Peru (Loayza and Rigolini 2016), poverty rates in Chile (Álvarez et al. 2018), or the negative externalities of mining in relation to the economic activity of other economic sectors through competition for key inputs (such as land and labor) and environmental pollution in Ghana (Aragón and Rud 2012).

this knowledge gap by analyzing the Chilean case, also considering the different impact of the shock across counties.

2 Theoretical framework

It is necessary to make use of the appropriate theoretical framework in order to illustrate the causal relationship that exists between an exogenous economic shock and schooling and youth labor force participation, using for this purpose the theory of human capital (Becker 1964). Assume an economy comprising two sectors which use labor only for production. Both sectors differ in terms of the intensity of the use of human capital. The firm's hiring decisions are defined by the maximization of their profit function[7] which equates labor productivity with salary: $y = w$ for a firm that operates in the jth sector.[8] Additionally, let us consider that labor productivity depends on the level of human capital accumulated by each hired worker $\left(h\left(\theta_j\right)\right)$, having:

$$y = A \cdot h\left(\theta_j\right) \tag{1}$$

θ_j being the number of years of schooling obtained $\left(\frac{\partial h(\theta_j)}{\partial \theta_j} > 0\right)$ and A the production efficiency of human capital. Using the solution of the profit maximization function and Eq. (1) we can establish:

$$w \equiv w\left(\theta_j\right) = A \cdot h\left(\theta_j\right) \tag{2}$$

Taking into account (2) and that the level of human capital increases with years of schooling, we can assume that there will be a positive wage difference in the market in favor of those workers who are more educated, having:

$$\Omega = w\left(\theta_{HS}\right) - w\left(\theta_{n-HS}\right) > 0 \tag{3}$$

The relationship obtained in (3) is expected when the market operates under normal conditions, which rewards higher levels of schooling. However, in the event of an exogenous economic shock or other type of disruption, the composition of the skill requirements for the labor market will be altered. The effect of such a shock will distort the value of schooling, affecting the decisions of individuals with respect to obtaining further education or joining the labor market.

To illustrate this, let us assume that a young individual of working age is faced with this decision.[9] Let us say that such an individual has a finite time horizon working life $t = 0, \dots, T$, comprising a specific number of years in which they can take

[7] For the sake of simplicity, we will assume that workers from one sector cannot move to a company belonging to another sector. We will also assume that the market price has a unit value.

[8] We will only consider two sectors in our analysis: (i) a sector which only operates with high-skilled workers ($j = HS$) and (ii) the remaining sector operating with only low-skilled workers ($j = n - HS$).

[9] In order to simplify the present analysis, we will assume that the individual cannot choose to work and study at the same time, and that once they decide to join the labor market then they cannot return to school.

part in the labor market until the age T, which corresponds to the last year worked in the labor market. In the case of making the decision to join the labor market and considering (2), the individual will be faced throughout their working life with an income defined by:

$$\int_{0}^{T} w\left(\theta_{n-HS}\right) \cdot e^{-r \cdot t} \cdot dt = \int_{0}^{T} A \cdot h\left(\theta_{n-HS}\right) \cdot e^{-r \cdot t} \cdot dt \tag{4}$$

where $w\left(\theta_{n-HS}\right)$ corresponds to the salary that would result from θ_{n-HS} years of schooling and r being the discount factor. Furthermore, if the individual decides to continue their education, he will have to meet the cost of acquiring the desired educational level θ_{HS} plus the time spent in education and therefore not receiving a salary, being the total cost defined by C (BMS 2005). In this way, the individual will be faced with an income expectative such as:

$$\int_{\theta_{HS}+1}^{T} w\left(\theta_{HS}\right) \cdot e^{-r \cdot t} \cdot dt + C = \int_{\theta_{HS}+1}^{T} A \cdot h\left(\theta_{HS}\right) \cdot e^{-r \cdot t} \cdot dt \tag{5}$$

The effect that shocks exert over the market has yet to be determined, however its impact is crucial in order to understand the changes that take place in such a market and how they affect schooling decisions. According to BMS (2005) 'a transitory shock that increases demand for low-skilled workers […] will temporarily raise the wages of high school dropouts relative to high school graduates. This increases the opportunity cost of young people to remain in school, and may decrease the wage gap between graduates and dropouts for the first year or so of work (p. 5),' while the same can be said about a positive shock that increases the demand for high-skilled workers.

Thus, let us suppose that an exogenous economic shock, independent of the sector in which it operates, alters the market temporarily and with it, the equilibrium salary level goes up due to an increase in labor demand. This fact has a positive impact on wages in the market for that sector $\left(w\left(\theta_j,\ s_j\right)\right)$, so that:

$$w\left(\theta_j,\ s_j\right) = w_0\left(\theta_j\right) + s_j \cdot \int_{a}^{b} \Delta w_0\left(\theta_j\right) \cdot dt \tag{6}$$

where $w_0\left(\theta_j\right)$ corresponds to the wage that a worker receives with θ_j years of schooling irrespective of the economic shock, $\Delta w_0\left(\theta_j\right)$ represents the absolute change in wages during the shock, s_j being a variable that can adopt three different values: (a) $s_j = 1$, when the shock has a positive impact on income, (b) $s_j = -1$, when the shock has a negative impact, and (c) $s_j = 0$, when the shock has no impact. Lastly, the parameters a and b identify the period of time of the shock over the economic sector and with it, its duration over the salary.

By using (3), (4), (5) and (6), we can identify the impact that the exogenous economic shock has on the performance of schooling in the market during working life, having:

$$\Omega = \gamma\left(s_{HS}\right) \cdot \left(\int_{\theta_{HS}+1}^{T} w\left(\theta_{HS},\ s_{HS}\right) \cdot e^{-r \cdot t} \cdot dt + C \right) - \gamma\left(s_{n-HS}\right) \cdot \int_{0}^{T} \left(w_0\left(\theta_j\right) + s_j \cdot \int_{a}^{b} \Delta w_0\left(\theta_j\right) \cdot dt \right) \cdot e^{-r \cdot t} \cdot dt \tag{7}$$

where $\gamma\left(s_{HS}\right)$ and $\gamma\left(s_{n-HS}\right)$ represent the perceived probability of being employed in the high- and low-skilled sectors, respectively. These probabilities depend positively on the exogenous economic shock $\left(s_j\right)$ because it increases production in that sector by raising the profit expectations of companies and with it the number of job vacancies posted (Petrongolo and Pissarides 2001). This increase in job-vacancies raises the probability of being employed during the entirety of the economic shock $\left(\frac{\partial\gamma\left(s_{HS}\right)}{\partial s_{HS}} > 0,\ \frac{\partial\gamma\left(s_{n-HS}\right)}{\partial s_{n-HS}} > 0\right)$.

The impact of the economic shock on (7), regardless of the sector in which it operates, will affect the incentives for the young person who has to decide between continuing their education and joining the labor market. Thus, the probability of a young person remaining in school (defined by the value $\phi = 1$) is subject to the value of (8.1) and (8.2), having:

$$\Pr\left[\phi = 1 | \Omega > 0\right] > 0 \tag{8.1}$$

$$\Pr\left[\phi = 1 | \Omega \leq 0\right] = 0 \tag{8.2}$$

With:

$$\phi = \begin{cases} 1\ (\textit{the individual remains in school}) \\ 0\ (\textit{the individual dropouts the school}) \end{cases}$$

The metal mining price boom positively affected the low and medium–low-skilled workforce of Chile's extractive activities as well as other sectors closely linked to internal demand, such as construction, trade and other services. The boost on these sectors was due to the positive effect that mining wages had on purchasing power, especially in those counties where mining had a greater bearing on production activity (Pellandra 2014; Rehner and Vergara 2014). This impact on sectors with a low- and medium–low-skilled workforce may have negatively affected school enrollment while the shock lasted due to the increase in salaries, similar to that shown in (8.2). This decrease in school enrollment should be accompanied by an increase in youth labor market participation, motivated by the lower skill premium for schooling. In this sense, the probability of youth labor market participation ($\Pr[\omega = 1]$])[10] should

[10] When $\omega = 0$, the individual doesn't participate in the labor market.

be understood as the complement of the probability of young people remaining in school ($\Pr[\omega = 1] = 1 - \Pr[\phi = 1]$).

3 Data and previous descriptive evidence

We will make use of the Chilean *National Socioeconomic Characterization Survey* (CASEN), developed by the Ministry of Social Development. The survey measures the socioeconomic conditions of the country's households at a regional and county level, although it only includes a certain number of counties, primarily those with a high population. The survey provides socioeconomic information such as salary, weekly working hours, educational level, status of the individual in the labor market, etc. The period to be analyzed will be the one corresponding to the years 2000–2015 and will utilize the 2000, 2003, 2006, 2009, 2011, 2013 and 2015 CASEN surveys.

In spite of the fact that the theoretical model previously developed is defined at an individual level, the empirical analysis will be carried out at a county level. Data aggregation will allow us to identify changes that occur from before, during and after the shock for the different Chilean counties, allowing for the creation of panel data (similar to that of BMS (2005)).[11] This will allow for an unbalanced panel for the analyzed period with an average of 257 counties for each year of the survey. Furthermore, we decide to aggregate the data at a county level since this is the smallest administrative unit in Chile and counties are the closest territorial division to a local labor market. Also, following Álvarez et al. (2018), we decide to aggregate the data instead of working at a household level, because in the latter it might be more challenging to identify general equilibrium effects like spillovers to sectors not directly related to the metal mining sector, for instance.

It is essential that we define a measure for identifying the intensity of the shock on the economy. For this purpose, we use the measure defined by Álvarez et al. (2018), who consider the price effect of all relevant metals in the Chilean economy for the period analyzed. The authors define a price index that considers the five principal metals in Chilean production (copper, silver, gold, molybdenum and iron ore).[12] They first define an average percentage change in the metal's price for each period t, as:

$$\tilde{P}_{t,m} = \sum_{l=1}^{5} \varphi_{l,m}^{2000} \cdot \frac{\Delta p_t}{p_t}$$

[11] The process of individual data aggregation requires the assumption that the individual behavior theoretically identified in Sect. 2 is the one that defines the behavior of the population average.

[12] According to Álvarez et al. (2018) 'these metals represent over 99.5% of the production value between 1998 and 2013. Copper is by far the most important: it accounts for over 85% of the total production value for each year (p. 4).'.

where l represents each of the five metals considered, $\varphi^{2000}_{l,m}$ is the production value share of each metal l in 2000[13] in every m Chilean region ($m = 1, \ldots, 15$) –we consider regions, since there is no disaggregated data at the county level (with $\sum_{i=1}^{5} \varphi^{2000}_{i,m} = 1$) and p_t is the nominal price of each one of the five metals. The price and production data for the primary metals produced in Chile were taken from the Chilean Mining Yearbook (Anuario de la Minería de Chile, AMC) provided by SERNAGEOMIN, in order have production figures that are disaggregated by region.

The metal price index is computed as (see Appendix 1, Figure 2 for more detail about the historical dynamic of the metal index at a national level, as compared with the series of employment in mining industry):

$$P_{t,m} = \left(1 + \tilde{P}_{t,m}\right) * P_{t-1,m}\ ,\ with\ P_{2003,m} = 100$$

This measure considers the intensity of the shock on the economy. However, we also have to differentiate the impact of the shock depending on the county since there is a greater effect on those that are metal mining producers. For this reason, we define two types of classification for categorizing counties as metal mining producers due to the inexistence of an official classification. The first one is also defined by Álvarez et al. (2018), who create a measure of exposure to the changes in $P_{t,m}$ (for each of the counties) taking into consideration the relative weight of employment in the metal mining sector with respect to the total for each county in the first year of the sample. In our case: year 2000. In this way, the interaction between both variables accounts for the effect of the metal mining boom in each county.

We create an alternative criterion to classifying metal mining counties as a robustness check, in order to test the validity of the results obtained by applying our first measure. We consider the data provided by the AMC[14] in order to get an approximation of the counties that are metal mining producers. The AMC provides annual information regarding the mines in operation for every county and for any type of resource exploited in Chile and is used for the years 2007, 2009, 2011, 2013 and 2015[15] in order to identify the counties that are metal mining producers. We create a dummy variable, and a value of 1 is given to a county that has at least one metal mine operating there during the period of analysis. Otherwise, a value of 0 is given. With this criterion, we identify 46 counties that are metal mining producers (see Appendix 1, Table 7 and Fig. 3).

It is important to consider that this alternative criterion only provides information about the existence (or not) of the exploitation. It does not provide information about the metal mining production or the level of employment in metal mining sector in the county. Nevertheless, this second criterion allows us to eliminate the effect of long-distance commuting (LDC)[16] by properly identifying the counties

[13] The first year of the sample is taken to avoid the potential existence of simultaneous causality in our estimates.

[14] See for example: http://www.sernageomin.cl/mineria/anuario-2016-sernageomin/.

[15] Unfortunately, due to a lack of information, there is no AMC information for 2000 or 2003.

[16] Long-distance commuting is a phenomenon related to individuals that work in a county/region different from that in which they live. In Chile, this phenomenon is important, particularly in counties in the

that are metal mining producers, something that is not possible with the measure of Álvarez et al. (2018). The Álvarez et al. (2018) measure considers all the workers employed in the metal mining sector, independent of whether their job is located in their county of residence. Including LDC to create the employment rate could distort the accuracy of the Álvarez et al. (2018)[17] measure used to identify the metal mining counties, resulting in counties with a high relative weight of employment in the metal mining sector with respect to the total, although there is no metal mining exploitation there. This is something which does not affect the AMC measure.

Figure 1 uses this new definition to identify the dynamics of the average for both the school enrollment rate and the youth labor force participation during the period analyzed, dividing the analysis between metal mining and non-metal mining producer counties. It also groups the analysis by age (a) 15–18 years and (b) 18–24 years, the first corresponding to individuals who should still be in compulsory education, but who can legally join the labor market. The results show that there are greater oscillations throughout the shock (the period between 2003 and 2011) in the analyzed variables for the first age group, and that these oscillations were particularly accentuated for metal mining producer counties. Between 2003 and 2009 the average school enrollment rate for the first age group in metal mining producer counties dropped from 86 to 78.3%, which was accompanied by an increase in labor participation from 9.6 to 15.5% in the same period. After 2009, the school enrollment rate in these counties tends to increase until exceeding the value reached in 2003, while labor participation is at lower levels than that year. In non-metal mining producer counties, we observe a less abrupt oscillation, although the school enrollment rate increased starting in 2009.

It should be noted that even though the shock started in the year 2003, its impact on school enrollment rates was felt years later, specifically in 2009 and nearly at the end of the shock's duration. As the shock persists over time, the perception of it being transitory becomes blurred and with it the perception that it will persist in the long term. This conditions the behavior of the agents, which in this case generates a negative effect on youth regarding their incentives for replacing education with labor participation, something that becomes more pronounced the longer the shock lasts (BMS 2005).

Regarding the 18–24-year-old age group, the changes tend to be smoother, although a similar behavior in the dynamics is observed for metal mining producer counties in the variables analyzed during and after the shock. What was described for the age groups analyzed would previously coincide with our theoretical approach.[18]

Footnote 16 (continued)

north of the country where it represents approximately 20–25% of total employment (Aroca and Atienza 2008).

[17] It is important to consider that the information provided by CASEN for the year 2000 does not allow us to identify LDC workers. Therefore, there is no variable capable of improving the accuracy of the employment rate in the metal mining sector.

[18] In addition, we performed an ANOVA to test whether the differences observed in Fig. 1 between the metal mining and non-metal mining producer counties are significant in both the school enrollment rate and labor force participation rate of young individuals. Our results indicate that these differences are

4 Empirical analysis

Continuing with the formulated theoretical framework, we will now evaluate if the events in the Chilean counties during the metal mining price boom have presented a similar behavior to what was proposed theoretically. We expect that the economic shock has modified the returns to schooling in the labor market for those metal mining producer counties. This modification has simultaneously altered the incentives for both schooling and youth labor participation in those counties. Thus, since the mechanism that transmits the shock on schooling enrollment and labor participation are the returns to schooling, we propose estimating a simultaneous equation model, having:

$$\text{rate\_school\_enr}_{vt} = \beta_0 + \alpha_m + \mu_t + \beta_1 \cdot \text{schooling\_returns}_{vt} + \varepsilon_{vt} \tag{9.1}$$

$$\text{rate\_part\_emp}_{vt} = \pi_0 + \omega_m + \tau_t + \pi_1 \cdot \text{schooling\_returns}_{vt} + v_{vt} \tag{9.2}$$

$$\begin{aligned}\text{schooling\_returns}_{vt} = \gamma_m + \lambda_1 \cdot z_{vt} + \lambda_2 \cdot \text{Ln}\left[P_{t,m}\right] + \lambda_3 \cdot z_{vt} \cdot \text{Ln}\left[P_{t,m}\right] \\ + \lambda_4 \cdot \text{emp\_rate\_dif}_{vt} + u_{vt}\end{aligned} \tag{9.3}$$

where the variable $\text{rate\_school\_enr}_{it}$, corresponds to the school enrollment rate for youth in the v^{th} county and the period $t = 2000,\ 2003,\ 2006,\ 2009,\ 2011,\ 2013,\ \mathit{and}\ 2015$, $\text{rate\_part\_emp}_{vt}$ is the labor force participation rate, and $\text{schooling\_returns}_{vt}$ represents the returns to schooling. In order to measure this last variable, we consider two different approaches: (1) by applying a Mincerian wage equation,[19] and (2) the difference between the

Footnote 18 (continued)

significant, in that metal mining counties have a higher rate of school enrolment and a lower rate of labor force participation in comparison with the other group. We have also performed an additional ANOVA to test if the two groups of counties considered present significant differences in the level of poverty. This new analysis is performed under the logic that poorer households might face budget constraints in keeping their children enrolled at school (Carneiro and Heckman 2002). The outcomes of this new analysis show that non-metal mining producer counties have a higher (and significant) level of both poverty and extreme poverty than the metal mining producers. These new results combined with the previous ANOVA indicate that the socioeconomic conditions in non-metal mining counties, particularly the higher level of poverty, is likely to affect the school attendance and labor participation of young individuals in these counties and might explain the differences observed between groups of counties in Fig. 1.

[19] To calculate this variable the following Mincerian wage equation will be estimated for each county, using the information available in CASEN for all the individuals that earn a salary in the county, correcting by sample selection bias:

$$\ln w_{i,v} = \alpha_0 + \alpha_1 \cdot \text{Year\_School}_{i,v} + \alpha_2 \cdot \text{Age}_{i,v} + \alpha_3 \cdot \text{Age}^2_{i,v} + \alpha_4 \cdot \text{Gender}_{i,v} + \theta_{h,v} + \lambda_{i,v} + u_{i,v}$$

i being each worker between 15 years old or over resident in a county v. The estimate includes years of schooling ($\mathit{Year\_School}_{i,v}$), age ($\mathit{Age}_{i,v}$) -as a proxy of the potential working experience in the labor market (Mincer 1974) and its square, individual's gender ($\mathit{Gender}_{i,v}$), the h^{th} economic sector in which he/she participates ($\theta_{h,v}$) and the Mills inverse ratio associated to the probability of being employed in the county ($\lambda_{i,v}$). To calculate this last variable a probit model is applied to identify the probability of being employed, using: years of schooling, age and its quadratic mean, gender and the number of people per household as regressors. This regression is applied to each of the counties in the different CASEN surveys used in the model; the predicted value being $\hat{\alpha}_1$ which will be identified as the variable $\mathit{schooling\_returns}_{vt}$ in (9.1, 9.2 and 9.3) (see Appendix 1, Table 9 which shows the yearly regional average of schooling returns estimated).

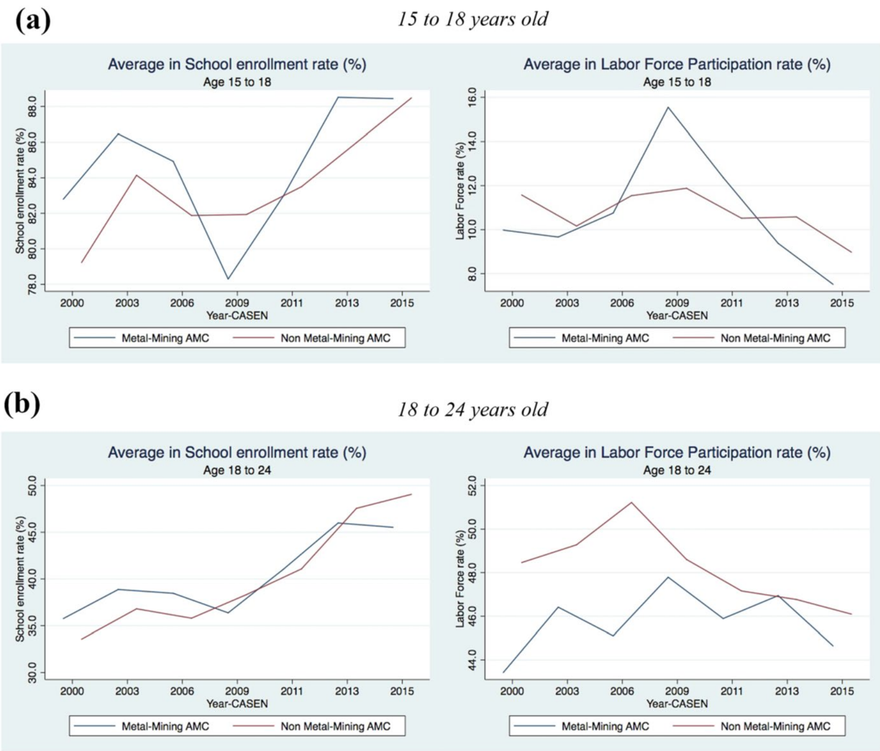

Fig. 1 Comparison of the dynamics for averages of school enrollment rates and labor force participation rates in both metal and non-metal mining producer counties between 2000 and 2015, using AMC criterion. The analysis groups the population by age *(a)* 15–18 years old and *(b)* 18–24 years old. *Source* Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015. Averages only consider counties with a population greater than 25,000 individuals, since the data provided by the CASEN for small-sized counties might not be representative (Modrego & Berdegué, 2015). As a result, an average of 19 counties have a population of at least 25,000 individuals and are identified as metal mining producers between 2000 and 2015

average salary obtained for high- and low-skilled workers in each county. In this sense, a high-skilled worker is classified as someone who has completed a university or technical education. Low-skilled are those that have completed at most a high school education. Therefore, a different estimate of Eqs. (9.1), (9.2) and (9.3) will be applied with each of the defined measures. The variables α_m, ω_m, and γ_m are regional fixed effects, μ_t, and τ_t being time fixed effects. The variable z_{vt} identifies each one of the two criteria previously considered to define a metal mining county. Finally, $\mathrm{Ln}\left[P_{t,m}\right]$ represents the price index defined in logs by region and the variable $\mathrm{emp\_rate\_dif}_{vt}$ defines the ratio between the employment rate of high- and low-skilled workers, this being a proxy of the probability that a high-skilled worker has of being employed with respect to a low-skilled worker.

In addition, it is important to highlight that (9.3) considers the exogenous economic shock ($\mathrm{Ln}\left[P_{t,m}\right]$) as an intervention impacting the country's metal mining counties (z_{vt}). Equations (9.1), (9.2) and (9.3) define a structural simultaneous equations system, rate_school_enr$_{vt}$, rate_part_emp$_{vt}$, and schooling_returns$_{vt}$ being the endogenous variables in the model. The system of equations presented in its structural form is very useful, since it allows us to estimate the impact of the shock on both school enrollment and youth labor participation through the returns to schooling. We use the 3SLS (instead of the 2SLS) methodology for solving this system of equations as it allows us to exploit the correlation of the disturbances across equations since there may be different unobserved elements that jointly affect e_{vt}, v_{vt}, and u_{vt}, thus improving the efficiency of the estimates.

Our main interest is focused on the coefficient associated with the interaction between the exogenous economic shock ($\mathrm{Ln}\left[P_{t,m}\right]$) and being a metal mining county (z_{vt}), i.e., the estimation of λ_3, since this isolates the impact of the shock via the returns to schooling in those counties. However, this coefficient does not completely measure the effect of the shock on both school enrollment and youth labor force participation. In order to have a measure of both effects, we need to estimate the product of $\lambda_3 \cdot \beta_1$ and $\lambda_3 \cdot \pi_1$, which is performed in the estimates through a non-linear combination of estimated coefficients in the model. The estimates of the simultaneous equations model are calculated for two different age groups: 15–18 and 18–24, divided by the same age group's population defined previously in the analysis of Fig. 1.

On the other hand, the estimates defined require controlling for a potential source of measurement error bias. This is because the sampling carried out by the CASEN for the counties with a small population size might not be representative of the selected variables in the analysis (Modrego and Berdegué 2015). This can introduce bias into the estimates, particularly when the regressors used show measurement errors. Thus, considering the following model for y_{vt}:

$$y_{vt} = \gamma_1 \cdot \tilde{x}_{vt} + \varepsilon_{vt}$$

where, $\tilde{x}_{vt} = x_{vt} + u_{vt}\left(N_{vt}\right)$ is an approximate measurement of the real value for x_{vt} which includes an error measurement $u_{vt}\left(N_{vt}\right)$, which depends on the size of the population where the sample is taken from, having to:

$$\lim_{N_{vt}\to\infty} u_{vt}\left(N_{vt}\right) = 0$$

Taking into consideration the aforementioned, the estimator $\hat{\gamma}_1$ works (Greene 2012):

$$plim\ \hat{\gamma}_1 = \frac{\gamma_1}{1 + \frac{\sigma^2_{u_{vt}}}{\sigma^2_{x_{vt}}}}$$

Therefore, the lower the population size $\left(N_{vt}\right)$ of observable units, i.e., counties, in the study, the greater the measurement error bias, and hence the limit of the calculated estimator $\hat{\gamma}_1$ which will converge in probability to a value close to 0. Usually, the way to correct a measurement error bias is the application of instrumental variables (Angrist and Krueger 2001). For this, appropriate instruments must be found which can correct the potential source of correlation between the endogenous variables and the model's residuals. This is extremely complex for the present study, since the source of error is in the sample developed for counties with a small population and not due to a wrong quantification of the variables used in the analysis.[20] To solve this potential source of endogeneity, three different estimates of the simultaneous equations model are proposed in terms of the population size of the counties considered in the study: (a) using the whole available sample, (b) considering only those counties with at least 25,000 inhabitants and (c) considering only those counties with at least 50,000 inhabitants. As a result, it is expected that the greater the population size of the analyzed observable units, the more stable the estimated coefficients are likely to be, reducing the impact of measurement error bias.[21]

5 Results

Table 1 shows the estimates of (9.1), (9.2) and (9.3) for the 15–18-year-old age group,[22] taking into consideration the relative weight of the employment held in the metal mining sector with respect to the total for each county in the first year of the sample, as a measure of a county's exposure to the economic shock (similar to Álvarez et al. (2018)). Likewise, this table takes into account the two measures proposed to define the returns to schooling (schooling_returns$_{vt}$), either through (1) its estimation via the calculation of the Mincer salary equation or (2) the difference between the average salary obtained for high- and low-skilled workers in each county. The estimates apply for three different sample subgroups (the entire sample of countries and those counties with a population of at least 25,000 and at least 50,000), in order to deal with the aforementioned measurement error bias.

All of the estimations show that the school enrollment rates and labor force participation rates were significantly affected by the returns to schooling, regardless of the measure used to calculate this variable. We observe that the increase in returns to schooling in the market improves enrollment for the 15–18-year-old age group in the period analyzed (see the estimates for Eq. (9.1)). At the same time, it also statistically and significantly discourages their participation in the labor market (see the estimates for Eq. (9.2)). These results are consistent with what is theoretically expected.

[20] The measurement error is due to the sample itself, therefore any variable (n_{vt}) originating from the analyzed database and used as an instrument would also carry with it a potential problem of error measurement, which would violate the orthogonality of the residues: $E\left(n_{vt} \cdot \varepsilon_{vt}\right) \neq 0$, which would limit the use of this technique.

[21] The elimination of counties with small populations from the estimates carried out will produce results that can only be valid for the sample under consideration. However, other authors have applied similar distinctions in their applied studies. Card (2001) analyzes the impact of migration on the local labor markets in the U.S. and includes only 175 of the biggest cities (out of a total of 324), due to a lack of migration data.

[22] See Appendix 1, Table 8 for descriptive statistics.

Table 1 3SLS estimates for 15–18-year-old individuals, using the relative weight of employment in the metal mining sector with respect to the total employment for each county in 2000 as the criterion to identify the counties most exposed to the shock (Álvarez et al., 2018). *Source* Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015.

Population	(1) Sch_return$_{it}$ estimated by Mincerian wage equation			(2) Sch_return$_{it}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Estimates of Eq. (9.1): rate_school_enr$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: β_1)	1.3223 (0.2255)***	1.4580 (0.2565)***	1.7251 (0.3459)***	0.0052 (0.0010)***	0.0026 (0.0006)***	0.0025 (0.0006)***
β_0	71.0079 (2.9031)***	72.3807 (4.8509)***	68.9958 (5.8733)***	70.2890 (3.8072)***	71.1841 (4.1963)***	71.1694 (4.1026)***
Estimates of Eq. (9.2):rate_part_emp$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: π_1)	−0.6277 (0.1593)***	−0.6308 (0.1636)***	−0.6386 (0.1949)***	−0.0021 (0.0005)***	−0.0010 (0.0004)***	−0.0008 (0.0003)**
π_0	14.7942 (2.0869)***	11.7417 (3.1920)***	11.9769 (3.3950)***	14.5512 (2.0123)***	11.7637 (2.7710)***	10.3787 (2.5275)***
Estimates of Eq. (9.3):schooling_returns$_{vt}$						
z_{vt}(using Álvarez et al. (2018) definition)	0.5582 (0.1508)***	0.7008 (0.2318)***	0.7595 (0.2499)***	117.5399 (78.5453)	317.6370 (110.3000)***	296.3672 (136.6847)**
$\mathrm{Ln}\left[P_{t,m}\right]$	0.7881 (0.1911)***	0.6517 (0.3373)*	1.1040 (0.3324)***	226.3621 (147.4855)	630.0525 (172.8364)***	766.4116 (194.7276)***
emp_rate_dif$_{vt}$	0.0350 (0.0044)***	0.0275 (0.0039)***	0.0217 (0.0038)***	8.3392 (3.4433)**	13.9172 (1.9923)***	13.2545 (2.0722)***
$z_{vt} \cdot \mathrm{Ln}\left[P_{t,m}\right]$ (coefficient estimated: λ_3)	−0.0812 (0.0273)***	−0.0944 (0.0419)**	−0.1180 (0.0436)***	−16.8049 (14.1302)	−45.4890 (19.6813)**	−48.3861 (23.9045)**
Observations	1798	861	539	1954	898	555

Table 1 (continued)

Population	(1) Sch_return$_{it}$ estimated by Mincerian wage equation			(2) Sch_return$_{it}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Interactions						
$\beta_1 \cdot \lambda_3$	−0.1074 (0.0412)***	−0.1376 (0.0671)**	−0.2036 (0.0836)**	−0.0873 (0.0754)	−0.1210 (0.0569)**	−0.1221 (0.0635)*
$\pi_1 \cdot \lambda_3$	0.0510 (0.0217)**	0.0595 (0.0311)*	0.0753 (0.0355)**	0.0354 (0.0312)	0.0495 (0.0269)	0.0394 (0.0258)

*: Statistically significant at the .10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (9.1) and (9.2) include both regional and time fixed effects in their estimates. Meanwhile, (9.3) only incorporates regional fixed effects

On the other hand, when analyzing the impact on the returns to schooling that the interaction between the economic shock and the relative weight of the employment held in the metal mining sector for the first year of the sample in each county, we observe a negative and significant effect for practically all the estimates (see the estimates for Eq. (9.3)). The effect of the shock combined with being a county that previously had high exposure to it significantly reduced the skill premium for schooling in the labor market during the period analyzed. Likewise, when analyzing the significance associated with the impact of the shock via returns to schooling using the school enrollment rate (the coefficient associated with the interaction $\beta_1 \cdot \lambda_3$) and the youth labor force participation rate ($\pi_1 \cdot \lambda_3$)), the impact was negative and significant in almost all the estimates for the coefficient associated with the interaction. An increase of one unit in the interaction between the weight of mining employment in the year 2000 and the metal price index (in logs) would reduce the school enrollment rate in the period analyzed between −0.0873 and −0.2036 percentage points on average.

To understand this estimated relationship, let's propose an example (see Table 2). Consider the Calama[23] and Diego de Almagro counties, which are those that presented the greatest percentage of metal mining employment in 2000, reaching 28.2% and 27.7%, respectively, and increases in the metal price index by a log of 2.22 and 2.46 units between 2003 and 2011 (the start and end of the shock). By multiplying the respective values of each county by the coefficient associated with $\beta_1 \cdot \lambda_3$ in each of the estimates made ((1) and (2)), we observe between −5.46 and −12.73 percentage point decrease in the school enrollment rate for Calama, and between −5.95 and −9.38 decrease for Diego de Almagro. These values are close to the decreases that were actually observed: −8.46 and −8.69 percentage points, respectively; figures that are equivalent to the reduction in the school enrollment rate between 2003 and 2011 for the 15–18-year-old age group in both counties.

The shock encouraged the youngest age group to enter the labor market, this effect being significant only when using the Mincer salary equation to calculate returns to schooling. This could be due to the fact that this measure is more accurate measuring the value of an education in the labor market with respect to the average salary difference obtained between high- and low-skilled workers. A 1 percent increase in the weight of mining employment in 2000 and the metal price index (in logs) would increase the labor participation rate on average between 0.0354 and 0.0753 percentage points during the period analyzed.

Likewise, when the same estimates are analyzed for the 18–24-year-old age group (see Table 3), a behavior similar to that described for the 15–18-year-old age group is observed, with a decrease in the school enrollment rate and a simultaneous increase in the labor force participation rate. However, the coefficients associated with the interactions $\beta_1 \cdot \lambda_3$ and $\pi_1 \cdot \lambda_3$ tend to be higher. If we compare the cases of Calama and Diego de Almagro again (see Table 2), we observe that the school enrollment rate for the 18–24-year old group in Calama decreased between −14.78 and −28.9 percentage points (Table 4), with an increase between 6.39 and 12.01

[23] County where the well-known Chuquicamata mine is located.

Table 2 Impact estimated for the Chilean counties of Calama and Diego de Almagro, two of the top-5 counties with the highest percentage of employment corresponding to the metal mining sector with respect to the total employment in 2000

County	Employment held in metal-mining sector in 2000 (%)	Growth in $\mathrm{Ln}[P_{t,m}]$ between 2003 and 2011	Returns to schooling[x]	Variation in rate_school_enr$_{vt}$ 2003–2011 $(\beta_1 \cdot \lambda_3)$				Variation in rate_part_enr$_{vt}$ 2003–2011 $(\pi_1 \cdot \lambda_3)$			
				Estimates Table 1			Real variation	Estimates Table 2			Real variation
				Whole sample	$\geq 25,000$	$\geq 50,000$		Whole sample	$\geq 25,000$	$\geq 50,000$	
Population between 15 and 18 years old											
Calama	28.2	2.218084	*(1)*	−6.71	−8.60	−12.73	−8.46	3.19	3.72	4.71	8.52
			(2)	−5.46	−7.56	−7.63		2.21	3.09	2.46	
Diego de Almagro	27.7	2.462636	*(1)*	−7.32	−9.38	−5.95	−8.69	3.47	4.05	5.13	14.43
			(2)	−5.95	−8.25	−8.33		2.41	3.37	2.68	
Population between 18 and 24 years old											
Calama	28.2	2.218084	*(1)*	−16.08	−19.19	−24.90	−10.99	7.40	9.19	12.01	9.48
			(2)	−14.78	−17.24	−18.38		6.39	8.19	8.89	
Diego de Almagro	27.7	2.462636	*(1)*	−17.53	−20.92	−27.16	−23.42	8.07	10.02	13.10	3240
			(2)	−16.12	−18.80	−20.05		6.97	8.93	9.70	

Source Self-elaborated with estimates from Tables 1 and 2. Both counties are selected because they present on average a population greater than 25,000 people during the period analyzed

[x] The method applied for calculating the returns to schooling are:

(1) schooling_returns$_{vt}$ estimated by Mincerian wage equation

(2) schooling_returns$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled worker

Table 3 3SLS estimates for the 18–24-year-old age group, using the relative weight of employment in the metal mining sector with respect to the total employment for each county in 2000 as the criterion to identify the counties most exposed to the shock (Álvarez et al. 2018)

Population	(1) Sch_return$_{it}$ estimated by Mincerian wage equation			(2) Sch_return$_{it}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	$\geq 25,000$	$\geq 50,000$	Whole sample	$\geq 25,000$	$\geq 50,000$
Estimates of Eq. (9.1): rate_school_enr$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: β_1)	4.2077 (0.5226)***	4.6489 (0.6293)***	5.8852 (0.9605)***	0.0191 (0.0031)***	0.0079 (0.0016)***	0.0079 (0.0015)***
β_0	6.98515 (6.3069)	13.6259 (11.0009)	−1.7874 (15.7808)	−2.0293 (12.0476)	16.2045 (8.3611)*	7.6296 (8.8110)
Estimates of Eq. (9.2):rate_part_emp$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: π_1)	−1.9385 (0.2944)***	−2.2277 (0.3541)***	−2.8394 (0.5196)***	−0.0083 (0.0014)***	−0.0037 (0.0008)***	−0.0038 (0.0008)**
π_0	55.9836 (3.6764)***	51.5780 (6.3972)***	58.3470 (8.6463)***	59.9418 (5.5191)***	50.9421 (4.8661)***	54.2521 (4.9414)***
Estimates of Eq. (9.3):schooling_returns$_{vt}$						
z_{vt}(using Álvarez et al. (2018) definition)	0.3570 (0.0923)***	0.4418 (0.1537)***	0.4150 (0.1664)**	83.1168 (41.5019)**	236.2701 (70.9969)***	225.5322 (83.9456)***
$\mathrm{Ln}\left[P_{t,m}\right]$	0.6334 (0.1695)***	0.5366 (0.3037)*	1.0198 (0.3088)***	196.6434 (127.7963)	460.7054 (148.6473)***	682.7903 (180.5260)***
emp_rate_dif$_{vt}$	0.0382 (0.0043)***	0.0298 (0.0038)***	0.0224 (0.0038)***	7.0001 (2.9591)**	16.0887 (1.7912)***	14.9641 (1.6300)***
$z_{vt} \cdot \mathrm{Ln}\left[P_{t,m}\right]$ (coefficient estimated: λ_3)	−0.0611 (0.0167)***	−0.0660 (0.0279)**	−0.0676 (0.0288)**	−12.3330 (7.0651)*	−34.7915 (12.2088)***	−37.1090 (14.5598)**
Observations	1798	861	539	1954	898	555

Table 3 (continued)

Population	(1) Sch_return$_{it}$ estimated by Mincerian wage equation			(2) Sch_return$_{it}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	$\geq 25,000$	$\geq 50,000$	Whole sample	$\geq 25,000$	$\geq 50,000$
Interactions						
$\beta_1 \cdot \lambda_3$	−0.2571 (0.0800)***	−0.3068 (0.1411)**	−0.3982 (0.1754)**	−0.2364 (0.1501)	−0.2757 (0.0942)***	−0.2940 (0.1058)***
$\pi_1 \cdot \lambda_3$	0.1184 (0.0382)***	0.1470 (0.0688)**	0.1921 (0.0860)**	0.1023 (0.0653)	0.1310 (0.0467)***	0.1422 (0.0534)***

Source Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015. *: Statistically significant at the .10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (9.1) and (9.2) include both regional and time fixed effects in their estimates. Meanwhile, (9.3) only incorporates regional fixed effects

percentage points in the labor force participation rate. In Diego de Almagro, these figures are −16.12 and −27.16 percentage points for the school enrollment rate and 6.90 and 13.10 percentage points in the labor force participation rate.

These first estimates show that the shock caused a reduction in the skill premium in the labor market, discouraging young people from continuing their education in order to participate in the job market. In order to contrast the robustness, the AMC criterion for classifying counties as metal mining or non-metal mining producers is used. The results show similar results for the two age groups analyzed. However, these tend to be mostly significant when the Mincer salary equation is used to define the returns to schooling ($\text{schooling\_returns}_{vt}$), since it is better suited for measuring this concept.

We observe for the 15–18-year-old age group that metal mining producer counties (under the AMC criterion) experienced a decrease in the school enrollment rate of between −0.9122 and −4.276 percentage points for each one percentage point increase of $P_{t,m}$. The labor force participation rate for this age group increased between 0.1358 and 1.2549 percentage points for said increase of one percentage point of $P_{t,m}$. Meanwhile (Table 5), for the 18–24-year-old age group we observe that their estimates show a greater effect, with the impact of the shock on the school enrollment rate for metal mining producer counties between −2.2031 and −7.4714 percentage points for each percentage point increase in $P_{t,m}$. Also, this shock produced a simultaneous increase in the labor force participation rate for the 18–24-year-old age group of between 1.0970 and 3.9731 percentage points for said increase of one percentage point in $P_{t,m}$ (see Table 6 for the predicted values of Diego de Almagro and Calama).

In summary, the results presented empirically validate the assumption that the metal mining price boom had a negative impact on returns to schooling which encouraged youth to join the labor market in those counties where metal mining activity is present.[24]

6 Conclusion

We analyze the impact that exogenous economic shocks have on both the school enrollment and labor participation rates of youth, particularly when the shock (while it lasts) alters the skill composition required by the labor market. We considered in our analysis the Chilean case during the metal mining price boom between 2003 and 2011. The immediate effect that the shock had on the Chilean economy was an increase in employment opportunities in not only the mining sector, but also other sectors which directly (construction) or indirectly (trade or

[24] Due to the importance of the copper mining industry in the Chilean economy we replicate our empirical analysis using the world price of copper as a measure for the intensity of the shock, thus creating a new measure for $Ln\left[P_{t,j}\right]$ in the simultaneous equations model estimated. The main results remain robust, but in some cases, we find a loss of significance, which can be explained by the lower variation of the copper price. All these additional estimates are available upon request.

Table 4 3SLS estimates for the 15–18-year-old age group, using the AMC criterion to identify counties that are metal mining producers

Population	(1) Sch_return$_{vt}$ estimated by Mincerian wage equation			(2) Sch_return$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Estimates of Eq. (9.1): rate_school_enr$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: β_1)	1.4846 (0.2400)***	1.4384 (0.2258)***	1.5149 (0.2425)***	0.0028 (0.0007)***	0.0018 (0.0003)***	0.0015 (0.0003)***
β_0	68.4995 (2.9507)***	67.3705 (3.6650)***	66.4836 (3.7704)***	72.7482 (2.5866)***	72.3312 (2.5952)***	73.9847 (2.4257)***
Estimates of Eq. (9.2):rate_part_emp$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: π_1)	−0.5876 (0.1630)***	−0.4343 (0.1414)***	−0.4446 (0.1462)***	−0.0011 (0.0003)***	−0.0005 (0.0002)**	−0.0002 (0.0002)
π_0	14.9809 (2.0325)***	12.5383 (2.3485)***	12.0345 (2.3253)***	13.1921 (1.5478)***	10.7159 (1.8188)***	9.2093 (1.6769)***
Estimates of Eq. (9.3):*schooling_returns$_{vt}$*						
z_{vt}(using AMC definition)	8.5557 (1.9827)***	13.0406 (3.0555)***	15.3910 (3.4853)***	2,701.1940 (1,271.252)**	4,078.653 (1,860.564)**	5,064.501 (2,523.198)**
$\text{Ln}\left[P_{t,m}\right]$	1.0528 (0.1809)***	1.3106 (0.2784)***	1.5236 (0.2640)***	285.4142 (144.0574)**	631.8754 (163.0632)***	666.4089 (179.6800)***
emp_rate_dif$_{vt}$	0.0199 (0.0026)***	0.0179 (0.0023)***	0.0158 (0.0021)***	10.3021 (2.1872)***	12.2355 (1.2730)***	12.5078 (1.3759)***
$z_{vt} \cdot \text{Ln}\left[P_{t,m}\right]$ (coefficient estimated: λ_3)	−1.5485 (0.3796)***	−2.3821 (0.5936)***	−2.8225 (0.6687)***	−470.5089 (239.5335)**	−499.3041 (361.3596)	−485.1127 (486.4499)
Observations	1996	894	565	2178	934	583

Table 4 (continued)

Population	(1) Sch_return$_{vt}$ estimated by Mincerian wage equation			(2) Sch_return$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Interactions						
$\beta_1 \cdot \lambda_3$	−2.2989	−3.4264	−4.2760	−1.3312	−0.9122	−0.7459
	(0.6866)***	(1.0103)***	(1.1859)***	(0.6865)*	(0.6839)	(0.7667)
$\pi_1 \cdot \lambda_3$	0.9099	1.0345	1.2549	0.5260	0.2498	0.1358
	(0.3405)***	(0.4244)**	(0.5018)**	(0.2997)*	(0.2125)	(0.1670)

Source Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015. *: Statistically significant at the .10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (9.1) and (9.2) include both regional and time fixed effects in their estimates. Meanwhile, (9.3) only incorporates regional fixed effects

Table 5 3SLS estimates for individuals of the 18–24-year-old age group, using the AMC criterion to identify the counties that are metal mining producers

Population	(1) Sch_return$_{vt}$ estimated by Mincerian wage equation			(2) Sch_return$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Estimates of Eq. (9.1): rate_school_enr$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: β_1)	4.7344 (0.5613)***	4.4165 (0.5321)***	4.8165 (0.6024)***	0.0090 (0.0020)***	0.0058 (0.0007)***	0.0050 (0.0006)***
β_0	−1.1185 (6.6898)	−1.6180 (8.3412)	−8.1144 (9.1672)	15.5230 (6.0709)**	11.6012 (5.3763)**	13.7303 (5.2287)***
Estimates of Eq. (9.2):rate_part_emp$_{vt}$						
schooling_returns$_{vt}$ (coefficient estimated: π_1)	−2.2792 (0.3222)***	−2.1520 (0.3120)***	−2.5613 (0.3708)***	−0.0045 (0.0010)***	−0.0028 (0.0004)***	−0.0028 (0.0004)***
π_0	60.1009 (3.9022)***	59.4363 (4.9744)***	63.2348 (5.6958)***	52.6340 (3.3722)***	53.4469 (3.2737)***	52.2962 (3.2922)***
Estimates of Eq. (9.3):schooling_returns$_{vt}$						
z_{vt}(using AMC definition)	5.8361 (1.2493)***	8.4459 (2.1856)***	8.6336 (2.5472)***	1432.276 (772.0053)*	3388.412 (1,375.373)**	3169.551 (1,881.568)*
$\mathrm{Ln}[P_{t,m}]$	0.8664 (0.1663)***	1.1652 (0.2710)***	1.4084 (0.2603)***	125.4254 (115.7296)	574.2298 (159.5340)***	609.8093 (177.6209)***
emp_rate_dif$_{vt}$	0.0195 (0.0026)***	0.0186 (0.0022)***	0.0162 (0.0021)***	10.5049 (2.1753)***	13.7009 (1.1949)***	14.4180 (1.2643)***
$z_{vt} \cdot \mathrm{Ln}[P_{t,m}]$ (coefficient estimated: λ_3)	−1.0616 (0.2394)***	−1.5697 (0.4246)***	−1.5512 (0.4834)***	−242.7552 (141.0171)*	−497.5292 (267.0057)*	−302.7946 (362.5350)
Observations	1,996	894	565	2,178	934	583

Table 5 (continued)

Population	(1) Sch_return$_{vt}$ estimated by Mincerian wage equation			(2) Sch_return$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled workers		
	Whole sample	($\geq 25,000$)	($\geq 50,000$)	Whole sample	($\geq 25,000$)	($\geq 50,000$)
Interactions						
$\beta_1 \cdot \lambda_3$	−5.0264 (1.3330)***	−6.9327 (2.0610)***	−7.4715 (2.4178)***	−2.2031 (1.1673)*	−2.8905 (1.6098)*	−1.5327 (1.8617)
$\pi_1 \cdot \lambda_3$	2.4198 (0.6683)***	3.3780 (1.0407)***	3.9731 (1.3157)***	1.0970 (0.5875)*	1.4248 (0.8012)*	0.8542 (1.0383)

Source Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015. *: Statistically significant at the .10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (9.1) and (9.2) include both regional and time fixed effects in their estimates. Meanwhile, (9.3) only incorporates regional fixed effects

Table 6 Impact estimated for the Chilean counties of Calama and Diego de Almagro, two of the top-5 counties that are metal mining producers using the AMC criterion

County	Growth in $\mathrm{Ln}[P_{t,m}]$ between 2003 and 2011	Returns to schooling[(x)]	Variation in rate_school_enr$_{vt}$ 2003–2011 ($\beta_1 \cdot \lambda_3$)				Variation in rate_part_enr$_{vt}$ 2003–2011 ($\pi_1 \cdot \lambda_3$)			
			Estimates Table 1			Real variation	Estimates Table 2			Real variation
			Whole sample	$\geq 25,000$	$\geq 50,000$		Whole sample	$\geq 25,000$	$\geq 50,000$	
Population between 15 and 18 years old										
Calama	2.218084	*(1)*	−6.63	−9.88	−12.33	−8.46	2.01	2.29	2.78	8.52
		(2)	−3.83	−2.63	−2.15		1.16	0.55	0.30	
Diego de Almagro	2.462636	*(1)*	−5.66	−8.43	−10.53	−8.69	2.24	2.54	3.09	14.43
		(2)	−3.27	−2.24	−1.83		1.29	0.61	0.33	
Population between 18 and 24 years old										
Calama	2.218084	*(1)*	−11.14	−15.37	−16.57	−10.99	5.36	7.49	8.81	9.48
		(2)	−4.88	−6.41	−3.39		2.43	3.16	1.89	
Diego de Almagro	2.462636	*(1)*	−12.37	−17.07	−18.40	−23.42	5.96	8.31	9.78	3240
		(2)	−5.42	−7.11	−3.77		2.70	3.50	2.10	

Source Self-elaborated with estimates from Tables 4 and 5. Both counties are selected because they present on average a population greater than 25,000 people during the period analyzed

[(x)] The method applied for calculating the returns to schooling are:

(1) schooling_returns$_{vt}$ estimated by Mincerian wage equation.

(2) schooling_returns$_{vt}$ calculated as the difference between the average salary obtained for high- and low-skilled worker.

consumer services) depended upon it, especially in parts of the country with high concentrations of mining. The exogenous shock not only boosted activity requiring a high- to medium-skilled workforce, but it also favored job creation in the low- or medium–low-skilled segment via a production-intensive workforce. Different authors (Pellandra 2014; Rehner and Vergara 2014) identify the later segment as having the most growth in employment during the shock.

We assess whether the effect of the shock on the labor market discouraged school enrollment rates among youth while simultaneously increasing their participation in the labor market. For this, a theoretical model was developed based on the classical theory of human capital which is subsequently empirically evaluated. The results show that the exogenous shock had a negative impact on returns to schooling in primarily metal mining producer counties. These counties present simultaneously both a negative impact on school enrollment rates and an increase in youth labor market participation. Additionally, this behavior is observed in those individuals who should legally be part of the educational system (the 15–18-year-old age group), introducing a risk for the economy primarily because of a negative effect on human capital accumulation, coupled with the decreasing employability of said youth in future. Something that may have boosted the level of unemployment in the counties highly exposed to the shock once this finished.

Appendix 1

See Figs. 2, 3 and Tables 7, 8, 9.

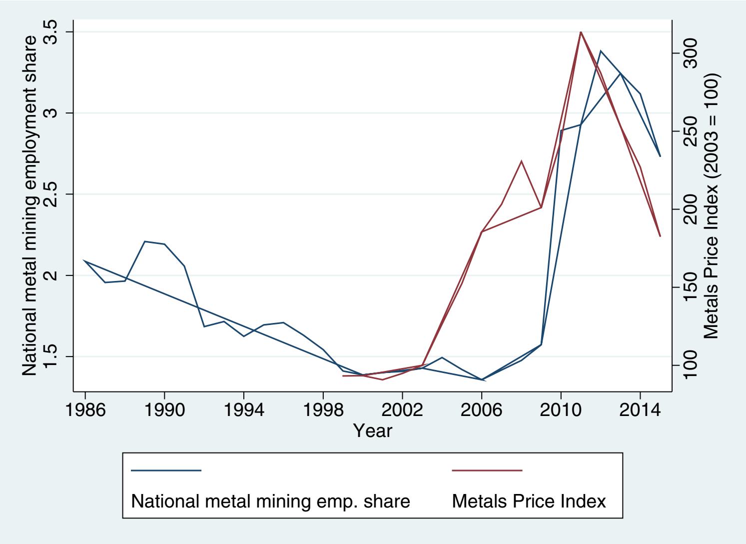

Fig. 2 Evolution for national average metal mining employment share between 1986 and 2015, and for national metal mining price index between 1999 and 2015. *Source* Self-elaborated using data from the National Labor Survey (ENE) and COCHILCO

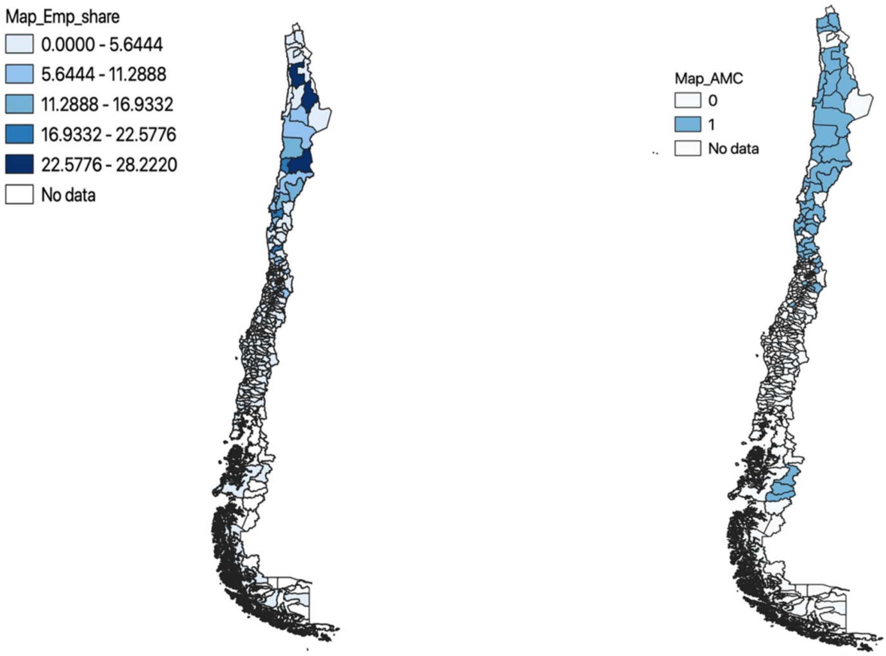

Figure (1) *Figure (2)*

Fig. 3 Chilean maps to identify the location of the metal mining producer counties, using both definitions used in the analysis. Figure 1 Relative weight of employment in the metal mining sector with respect to the total employment (Álvarez et al. 2018, Fig. 2) AMC definition. *Source*: Self-elaborated using CASEN database. *Note* Figure 1 shows the average county employment share for the year 2000. "No data" registers the counties not originally considered in the sample provided by the CASEN

Table 7 Mining counties considered in the analysis using the AMC classification criterion. *Source*: Self-elaborated

Pozo Almonte	Diego de Almagro	Los Andes	Camarones
Pica	Vallenar	Cabildo	Putre
Antofagasta	La Serena	Petorca	Chile Chico
Mejillones	Coquimbo	La Calera	Huasco
Sierra Gorda	Andacollo	Nogales	La Ligua
Taltal	La Higuera	Machalí	Los Vilos
Calama	Vicuña	Requínoa	Pencahue
Tocopilla	Illapel	Coihaique	Rancagua
María Elena	Salamanca	Río Ibáñez	Río Hurtado
Copiapó	Ovalle	Lo Barnechea	San Esteban
Tierra Amarilla	Monte Patria	Alhué	
Chañaral	Punitaqui	Arica	

Table 8 Mean and standard deviation (in brackets) for the variables used in empirical analysis. *Source* Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013 and 2015

Population	Whole sample	$(\geq 25,000)$	$(\geq 50,000)$
rate_school_enr$_{vt}$(15–18 years old)	83.13 (9.24)	83.83 (8.04)	84.76 (7.45)
rate_school_enr$_{vt}$(18–24 years old)	35.95 (13.42)	40.52 (13.57)	43.82 (13.61)
schooling_returns$_{vt}$(Mincerian wage equation)	7.53 (6.13)	8.83 (5.49)	9.70 (5.21)
schooling_returns$_{vt}$(difference between the average salary obtained for high- and low-skilled workers)	3414.66 (5209.08)	3530.55 (3243.86)	3783.69 (3580.51)
rate_part_emp$_{vt}$(15–18 years old)	10.93 (7.44)	10.73 (6.17)	10.41 (5.69)
rate_part_emp$_{vt}$(18–24 years old)	48.08 (10.63)	47.84 (9.67)	47.69 (9.91)
z_{vt}(using Álvarez et al., (2018) definition)	1.55 (4.36)	1.46 (4.40)	1.45 (3.99)
z_{vt}(using AMC definition)	317[a] (14.52%)[b]	134[a] (14.52%)[b]	82[a] (14.07%)[b]
$\mathrm{Ln}\left[P_{t,m}\right]$	4.95 (0.45)	4.95 (0.40)	4.97 (0.40)
emp_rate_dif$_{vt}$	19.89 (51.47)	32.83 (76.36)	44.11 (94.55)

[a] Total number of cases

[b] Relative frequency

Table 9 Yearly regional average of schooling returns estimated in Mincerian wage equation *Source* Self-elaborated

Region	CASEN						
	2000	2003	2006	2009	2011	2013	2015
Tarapacá	13.13	4.95	6.14	9.05	10.81	5.79	11.19
Antofagasta	10.98	7.90	7.69	6.81	7.29	9.43	14.19
Atacama	5.54	8.42	8.78	5.06	6.57	8.51	6.18
Coquimbo	6.83	8.86	5.30	4.89	6.93	4.77	7.66
Valparaíso	8.21	7.46	5.57	5.75	7.83	6.48	9.10
O'Higgins	5.72	5.72	5.12	4.62	3.43	4.16	7.67
El Maule	8.15	5.45	5.21	5.98	3.55	5.29	7.84
El Biobío	9.35	7.95	8.27	7.44	7.06	4.64	11.45
La Araucanía	8.79	9.71	9.15	5.69	7.64	8.14	9.94
Los Lagos	8.78	6.95	7.48	9.30	10.39	9.17	8.29
Aysén	11.82	13.76	6.84	5.53	10.28	7.89	10.34
Magallanes	9.27	9.96	9.83	13.01	12.67	8.87	9.60
Metropolitana	10.24	9.80	8.47	7.61	8.29	8.34	8.67
Los Ríos	8.82	11.94	8.51	9.67	7.39	6.89	10.16
Arica y Parinacota	7.78	8.19	6.06	3.27	14.38	5.29	6.24

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References

Álvarez R, García-Marín A, Ilabaca S (2018) Commodity price shocks and poverty reduction in Chile. Resour Policy. https://doi.org/10.1016/j.resourpol.2018.04.004

Angrist J, Krueger A (2001) Instrumental variables and the search for identification: from supply and demand to natural experiments. J Econ Perspect 15(4):69–85

Aragón F, Rud J (2012) Mining, pollution and agricultural productivity: evidence from Ghana. Econ J. https://doi.org/10.1111/ecoj.12244

Aroca P, Atienza M (2008) La conmutación regional en Chile y su impacto en la Región de Antofagasta. Revista Latinoamericana De Estudios Urbanos Regionales 34(102):97–121

Becker G (1964) Human Capital. Columbia University Press for the National Bureau of Economic Research, New York

Black DA, McKinnish T, Sanders S (2005) Tight labor markets and the demand for education: evidence from the coal boom and bust. Ind Labor Relat Rev 59(1):3–16

Calero C, Bedi A, Sparrow R (2009) Remittances, liquidity constraints and human capital investments in Ecuador. World Dev 37(6):1143–1154

Card D (2001) Immigrant inflows, native outflows, and the local market impacts of higher immigration. J Law Econ 19(1):22–64

Carneiro P, Heckman J (2002) The evidence on credit constraints in post-secondary schooling. Econ J 112:989–1018

Ferreira F, Schady N (2009) Aggregate economic shocks, child schooling, and child health. World Bank Res Obs 24(2):147–181

Funkhouser E (1999) Cyclical economic conditions and school attendance in Costa Rica. Econ Educ Rev 18(1):31–50

Goldin C (1999) Egalitarianism and the returns to education during the great transformation of American Education. J Polit Econ 107(6):65–94

Greene W (2012) Econometric Analysis, 7th edn. Pearson, New York

Loayza N, Rigolini J (2016) The local impact of mining on poverty and inequality: evidence from the commodity boom in Peru. World Dev 84:219–234

Mckenzie D (2003) How do households cope with aggregate shocks? evidence from the Mexican Peso Crisis. World Dev 31(7):1179–1199

Mincer J (1974) Schooling, Experience, and Earnings. National Bureau of Economic Research, New York

Modrego F, Berdegué J (2015) A large-scale mapping of territorial development dynamics in Latin America. World Dev 73:11–31

Observatorio Laboral para la Región de Antofagasta (OLAB) (2016) Panorama Regional Antofagasta, OLAB, Servicio Nacional de Capacitación y Empleo (Chile)

Pellandra A (2015) The commodity price boom and regional workers in Chile: a natural resources blessing? Working Paper Lacerlacea, https://pdfs.semanticscholar.org/5ecf/4f0764da5971bbccc66bb1a8ed8731055fa6.pdf

Petrongolo B (2001) Pissarides C (2001) Looking into the black box: a survey on the matching function. J Econ Lit 39:390–431

Radetzki M, Eggert R, Lagos G, Lima M, Tilton J (2008) The boom in mineral markets: how long might it last? Resour Policy 33(3):125–128

Rehner J, Vergara F (2014) Efectos recientes de la actividad exportadora sobre la reestructuración económica urbana en Chile. Revista De Geografía Norte Grande 59:83–103

Schady N (2004) Do macroeconomic crises always slow human capital accumulation? World Bank Econ Rev 18(2):131–154

Singleton K (2013) Investor flows and the 2008 boom/bust in oil prices. Manage Sci 60(2):300–318

Willis RJ, Rosen S. (1979) Education and Self-selection. Journal of Political Economy. Special Number Part 2: Education and Income Distribution. 87(5): s7-s36

Zarkin GA (1983) Cobweb vs rational expectations models. Econ Lett 13:87–95