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Youth unemployment during economic shocks: Evidence from the metal-mining prices super cycle in Chile

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ABSTRACT

We analyze the effect of an exogenous commodity shock on youth long-run unemployment, and the causal mechanisms that underlie this relationship. We use Chile as a study case and the Metal Mining Price Super Cycle between the years 2003 and 2011 as an exogenous shock. The shock in Chile has two primary phases: expansion and contraction. Expansion began in 2003 and coincides with the sustained increase in metal mining prices, reaching their maximum level in 2011. Contraction began in 2013 as prices began to fall. The Chilean labor market was significantly affected by both. We leverage the heterogeneous spatial exposure of Chilean municipalities to the shock and use a difference-in-difference approach and simultaneous equations models with lagged variables to analyze the causal mechanisms. We find evidence that this shock negatively impacted the wage premium for education. We also provide empirical evidence of a simultaneous decrease in school enrollment rates and an increase in the labor force participation of the 15-18-year age group in mining municipalities during the shock. Finally, in the long term, this negatively impacted the employability of these individuals, increasing their likelihood of unemployment once the shock ended.

1. Introduction

Countries rich in natural resources tend to have undiversified economies (Arias et al., 2014), making them more vulnerable to the volatility of prices (Poelhekke and van der Ploeg, 2007). Local labor markets also tend to present disparities in terms of factor productivity, innovation, employment, and wages (Pellandra, 2015). Therefore, the aim of this study is to estimate the causal effect of a commodity shock on long-run unemployment, analyzing the causal mechanisms that underlie this relationship. We use the case of Chile, a metal-rich country, and the exogenous metal mining prices super cycle (MMPSC) shock that occurred between 2003 and 2011.

The MMPSC in Chile has two primary phases: expansion and contraction. Expansion began in 2003 and coincides with the sustained increase in metal mining prices, reaching their maximum level in 2011. Contraction began in 2013 as prices began to fall. The Chilean labor market was significantly affected by both. During expansion the country (and especially low-skilled segments) experienced growth in both employment and wages (Pellandra, 2015). During contraction, unemployment increased in those municipalities more exposed to the economic shock (those with a higher share of mining activity).

The MMPSC was largely a result of increased Chinese demand (Radetzki et al., 2008; Farooki and Kaplinsky, 2013), and the impact of speculation in the stock market due to investor flows (Singleton, 2014). Global supply was not a factor; therefore, we argue that the MMPSC is an exogenous shock for Chile, and ideal for use as a quasi-experiment. Commodity shocks have a negative effect on economic activity, especially in the long run. The resource curse literature suggests that those countries with an abundance of natural resources will have less economic growth and worse development than countries with fewer natural resources (Corden, 1984; Krugman, 1987; Sachs and Warner, 1995; Bebbington et al., 2008; Berman et al., 2017).

However, recent empirical studies have challenged this view. Drechsel and Tenreyro (2018), for example, find that commodity price shocks positively contribute to growth in output, consumption, and investment in Argentina from 1900 to 2015. Abaidoo and Agyapong (2022) analyze the effect that fluctuations in prices of different commodities have on inflation, inflation uncertainty and political stability among emerging economies in Sub-Saharan Africa from 1996 to 2019. They find that volatility in the price of crude oil, copper, and coal negatively affects the political stability of this region, while volatility in the price of gold and natural gas have a positive effect on these same

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outcomes.

In Chile, Álvarez et al. (2021) examine the impact that the MMPSC had on poverty and find that there was at least a 2% reduction of poverty in municipalities exposed to the shock. Chavez and Rodríguez-Puello (2022) analyze the effect of this same commodity shock on the gender wage gap and find evidence of a significant reduction in municipalities more exposed to the shock in comparison to municipalities with less exposure. Atienza and Modrego (2019) find that the expansion phase of MMPSC significantly benefited mining municipalities in terms of business formation and growth. However, they also found that the contraction phase negatively affected the whole group of suppliers independent of their location. Our study adds new evidence to the empirical debate of whether commodity shocks exert positive or negative effects on different economic dimensions. We focus on Chile, the world's largest producer of copper, the second largest producer of lithium, and the fourth largest producer of silver (in 2021).

The classical theory of human capital predicts that an increase in wages of low-skilled labor relative to that of high-skilled labor (a decrease in the wage premium for education), will cause individuals to acquire less schooling (Becker, 1964; Black et al., 2005). The expansion phase of the MMPSC in Chile is illustrative of this same causal mechanism, resulting in declining school enrollment due to the high opportunity cost between continuing education or joining the labor force (Pérez-Trujillo and Rodríguez-Puello, 2021). The decrease in school enrollment during the expansion phase in Chile resulted in dropouts once the shock ended, being the low-skilled workers those less likely to maintain their employment during the contraction (International Labor Office, 2018). This effect was not homogenous; mining regions had worse unemployment rates in the aftermath of the MMPSC shock (Daher et al., 2017).

Chile is an interesting case study because its economy and growth over the last four decades is highly concentrated in the exploitation and exportation of natural resources (Figueroa and Calfucura, 2003). According to the Observatory of Economic Complexity,[1] copper is one of the most traded products in the world, and Chile is its largest exporter. Chile produced 37% of the world's copper in 2016, and it represents about 29% of the world's total copper reserves (OECD, 2018). 52,1% of Chile's national exports between 2010 and 2016 were from mining, and this dependence on exports represents a significant vulnerability to external shocks.

This research has various contributions. First, it considers whether natural resources are actually a resource curse. It also provides empirical evidence regarding the mechanisms through which a commodity prices shock impacts the unemployment rate. Relevant empirical evidence can be instrumental in the design of policies and measures aimed at the stability of labor market conditions, economic shock preparedness and government response capacities.

We analyze the period from 2000 to 2017 using information from the 2000, 2003, 2006, 2009, 2011, 2013, 2015 and 2017 Chilean National Socioeconomic Characterization Survey (CASEN), developed by the Ministry of Social Development. We leverage the heterogeneous spatial exposure of municipalities to the shock (Álvarez et al., 2021) and we use a difference-in-difference (DID) approach and simultaneous equations models with lagged variables to analyze the causal mechanisms.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the data and the empirical strategy while section 4 presents descriptive evidence. Section 5 covers the main results and robustness checks, and Section 6 concludes the research and discusses policy implications derived from the main findings.

[1] See The Observatory of Economic Complexity (2022).

2. Literature review

To date, empirical literature that analyzes the impacts of exogenous economic shocks has mostly focused on the opportunity costs between schooling and participating in the labor market, and typically within the context of economic crisis (Goldin, 1999; Schady, 2004; Pérez-Trujillo and Rodríguez-Puello, 2021). The results of these studies are ambiguous. Some find that negative economic shocks e.g., the Mexican peso crisis, generate a positive effect on school enrollment due to a reduction in the opportunity cost between education and working (Mckenzie, 2003; Schady, 2004). Other studies find that these shocks negatively impact household income, resulting in youth dropping out and joining the labor force in order to contribute to their household income (Calero et al., 2009; Funkhouser, 1999). Ferreira and Schady (2009) explain this ambiguity: the income level in each economy is an important determinant of either a positive or negative effect of a crisis on school enrollment. In low-income countries, the authors find evidence of an income effect; a negative economic shock results in youth dropping out in order to gain employment and contribute to their household income. The effect in high-income economies is the opposite; a lack of opportunities in the labor market for youth motivates them to stay in school.

Regarding specific natural resource (mining) shocks, previous studies analyze the impact of mining on different outcomes such as poverty (Álvarez et al., 2021), gender gaps (Guimbeau et al., 2020), mining services suppliers (Atienza and Modrego, 2019), the formation of human capital under weak institutions (Agüero et al., 2021), among other topics. However, few studies analyze the impact of a natural resource export boom on the schooling and labor force participation of youth. The first of these innovative studies was developed by Black et al. (2005) and the authors focus on the Appalachian coal boom and bust, studying the impact of the shock on high school enrollment in Kentucky and Pennsylvania. The boom generated an increase in both the labor participation and salaries of low-skilled workers in the mining sector, and it also reduced the value that individuals placed on schooling, generating a reduction in high school enrollment. Measham and Fleming (2014) analyze the impacts of coal seam gas (CSG) development on rural community decline in Queensland, Australia between 2001 and 2011. They found that regions with CSG development saw a higher proportion of youth with university degrees and advanced technical training compared to other rural regions without gas development. Bonilla (2020) studies the case of Colombia, where gold production tripled between 2001 and 2014. The author finds that the gold boom increased primary school enrollment and reduced dropout rates at all school levels. He also finds that males between 19 and 25 years of age were more likely to work in mining during the boom period. Morissette et al. (2015) exploited the variation in youth wages induced by increases in world oil prices that took place during the period from 2001 to 2008 to estimate the elasticity of young men's labor market participation and school enrollment. To do this they use Canada as a case study. They found that the increased wages due to the shock had a dual impact on youth (17–24 years old) behavior: (i) They tended to reduce full-time university enrollment rates but also (ii) brought into the labor market some of those young individuals who were neither enrolled in school nor employment. Nevertheless, they also found little evidence that young men with no high school diploma left the school in response to increase in wages during the shock.

Recently, Pérez-Trujillo and Rodríguez-Puello (2021) analyzed the impact of the MMPSC on Chilean youth schooling enrollment and labor force participation. The authors found evidence that the shock reduced the wage premium of education, particularly in those municipalities that are metal-mining producers. The decrease in said wage premium reduced the rate of school enrollment of the youngest individuals of legal employment (aged between 15 and 18), while simultaneously increasing their workforce participation.

In spite of this evidence, there is a knowledge gap pertaining to economic shocks in mining on long-run unemployment. This study contributes to this gap. These shocks seem to create incentives for abandoning education, therefore negatively impacting the employability of dropouts when the shock inevitably ends.

It is important to highlight that the Chilean labor market was directly affected by the MMPSC. During the expansion phase 1 million new jobs[2] were added, many of them in the north, as employment rates there exceeded the national average. However, these were primarily low or medium-low-skilled positions, and most were either directly related to the mining sector or else within construction, retail, trade and other services that were indirectly benefited by the shock (Rehner and Vergara, 2014).

The salary boom also had an impact in terms of its distribution between skilled and unskilled workers in the areas more exposed to the shock (Pérez-Trujillo and Rodríguez-Puello, 2021). Pellandra (2015), who analyzes the impact of the MMPSC shock on local wages and employment levels for the Chilean provinces during the expansion phase (2003–2011) found that those provinces more exposed to the shock experienced an increase in the wages of low-skilled workers.

Furthermore, Atienza and Modrego (2019) analyzed the local effects of the MMPSC on the Chilean mining services suppliers. Their findings suggest that the expansion phase benefited suppliers in only mining municipalities while the contraction phase had the opposite effect on suppliers in both mining and non-mining municipalities. This study could be the starting point for fully understanding the potential negative impact of the shock on unemployment in the long run, particularly for workers in the metal mining industry during expansion. At the end of the expansion phase, Chilean GDP growth had cooled to under 3.0%, resulting in less dynamism in job creation (International Labor Office, 2018). As a consequence, unemployment grew steadily between 2014 and 2017, increasing by 15.1%, and particularly affecting those regions in which the mining extractive industry plays a larger role. For example, unemployment in the Region of Antofagasta (responsible for 16% of global copper production) nearly doubled (87.3%) between 2014 and 2017,[3] a clear outlier when compared to the national average. Similarly, unemployment grew by 34.6% in the same period (double the national rate) in the Region of Atacama.

3. Data and empirical strategy

The primary dataset used in this paper is the Chilean National Socioeconomic Characterization Survey (CASEN), developed by the Ministry of Social Development. This survey includes repeated cross sections of households, which are representative of the Chilean population at a regional and municipality level, and which provides household socioeconomic information such as: salary, weekly working hours, educational level, status of the individual in the labor market, etc. We analyze the period from 2000 to 2017 using the information from the 2000, 2003, 2006, 2009, 2011, 2013, 2015 and 2017 CASEN surveys. Following Álvarez et al. (2021) and Pérez-Trujillo and Rodríguez-Puello (2021), the empirical analysis is carried out at a municipality level, allowing us to identify changes that occurred during and after the MMPSC. This also allows us to create unbalanced panel data for the period. The CASEN includes survey information for approximately 257 municipalities per year with an average survey population of 210,679.

In our analysis it is necessary to define both the intensity of and a level of exposure to the MMPSC measure for each municipality in order to identify its impact on long-run unemployment. Regarding the level of exposure, we create a measure to classify municipalities as either mining or non-mining since the shock was a heterogeneous phenomenon without an official classification. We define two different measures of exposure to the shock:

(i) Weighted employment measure: Following Álvarez et al. (2021), the relative weight of employment of the metal mining sector with respect to total employment for each municipality in the year 2000.[4]

(ii) AMC measure: We create an alternative criterion to classify metal mining municipalities in order to test the validity of the results obtained by applying our first measure. To do so, we create a dummy variable with a value of 1 when a municipality has at least one metal mine operating during the period of analysis, and a value of 0 otherwise. This information comes from the data provided by the Chilean Mining Yearbook (Anuario de la Minería de Chile, AMC) provided by SERNAGEOMIN (see Pérez-Trujillo and Rodríguez-Puello, 2021).[5]

Fig. 1 shows the location of metal mining and non-mining municipalities using both measures of exposure. Panel (1a) depicts the classification using our first measure, which is the average employment share in each municipality for the year 2000. Panel (1b) shows the classification according to our AMC alternative measure. Regardless of the measure used, metal mining municipalities where the MMPSC had the largest impact are overwhelmingly located in the north of Chile.

Regarding the measure for identifying the intensity of the MMPSC on mining and non-mining municipalities, we follow Álvarez et al. (2021) who define a price index for the five principal metals of Chilean production: copper, silver, gold, molybdenum, and iron ore. We first create a price index to calculate the average percentage change in the price of a metal for each period t, as:

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

Where l represents each of the five metals considered, $\varphi_{l,m}^{2000}$ is the production value share of each metal l in 2000 in every m Chilean region. We use regions as there is no disaggregated data for production at the municipality level (with $\sum_{i=1}^{5} \varphi_{i,m}^{2000} = 1$). Finally, p_t is the nominal price of each of the five metals. The corresponding price and production data come from the Chilean Mining Yearbook (Anuario de la Minería de Chile, AMC) provided by SERNAGEOMIN, which provides production values that are disaggregated at a regional level.

The second step in the construction of this measure is to compute the metal's price index $P_{t,m}$ as:

$$P_{t,m} = \left(1 + \widetilde{P}_{t,m}\right) * P_{t-1,m} \text{ } with \text{ } P_{2003,m} = 100 \tag{2}$$

The metal mining price index is represented in Fig. 2, and clearly shows the phases of the shock. The years before 2003 are considered pre-shock, while after 2003 (the beginning of the expansion phase) we can observe a pronounced increase in the price index values. The maximum was reached in 2011, with a value that is more than twice the 2003 value. After 2011 the prices started to decline.

The interaction between the price index and the measures of exposure allows us to estimate the local impact of the MMPSC shock in each municipality, differentiating between those more or less exposed. The identification of these parameters of interest is based on both the variation of our main outcomes and the heterogeneous distribution of exposure in municipalities over time. This under the identifying assumption that in the absence of the shock, the variables would have followed a similar trend in both mining and non-mining municipalities.

[2] Author's own calculation based on data from 2003 to 2011 Labor Force Survey from the Chilean National Statistics Institute (INE).

[3] Growth is calculated via the average of the unemployment level from the quarterly National Labor Force Survey (ENE).

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

[5] Unfortunately, there is no AMC information for 2000 or 2003.

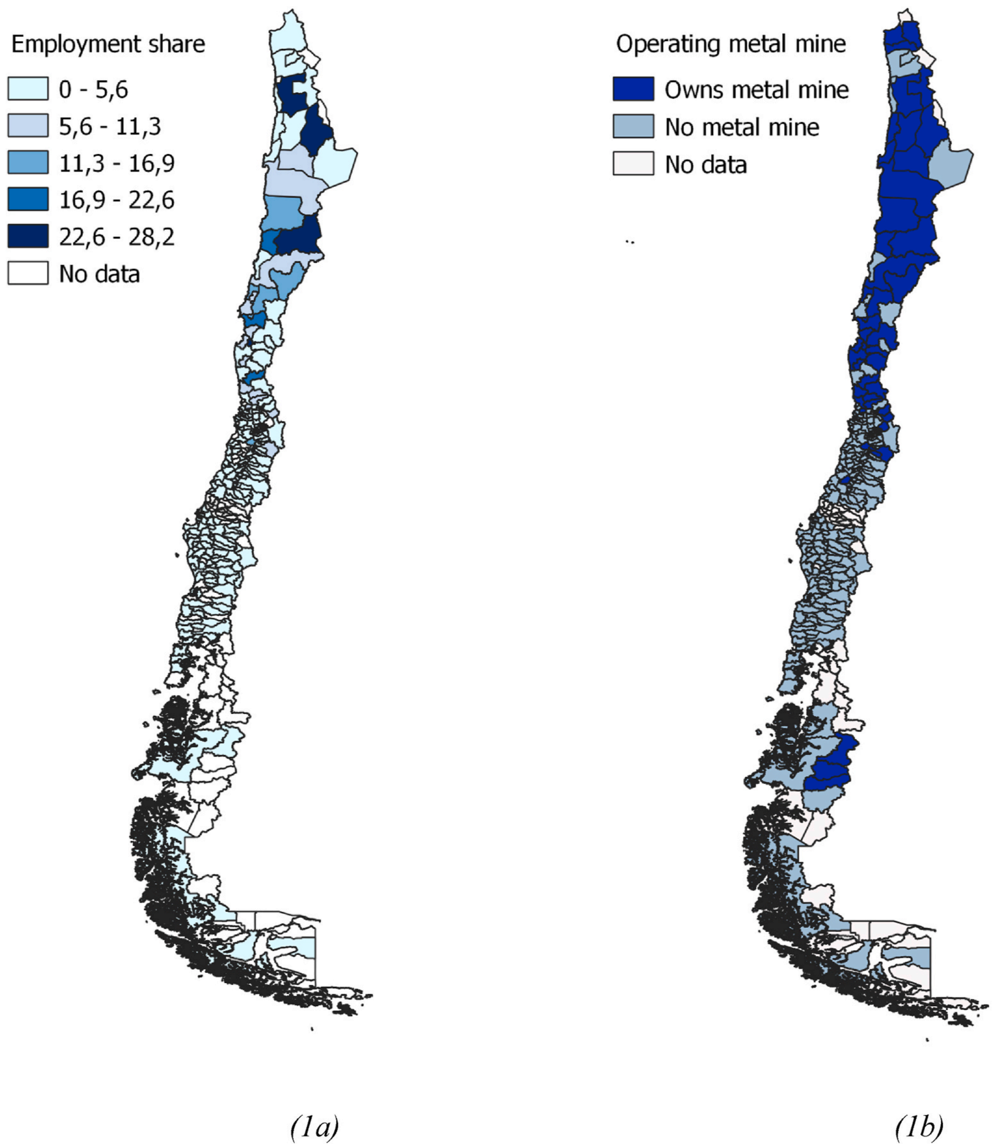


Fig. 1. Location of metal mining producer municipalities in Chile using both measures.
Source: Self-elaborated using CASEN database.
Note: Figure (1a) shows the average share of employment at a municipality level for the year 2000. Figure (1b) shows municipalities that have at least one metal mine operating during the period of analysis. "No data" considers those municipalities not originally considered in the sample provided by the CASEN.

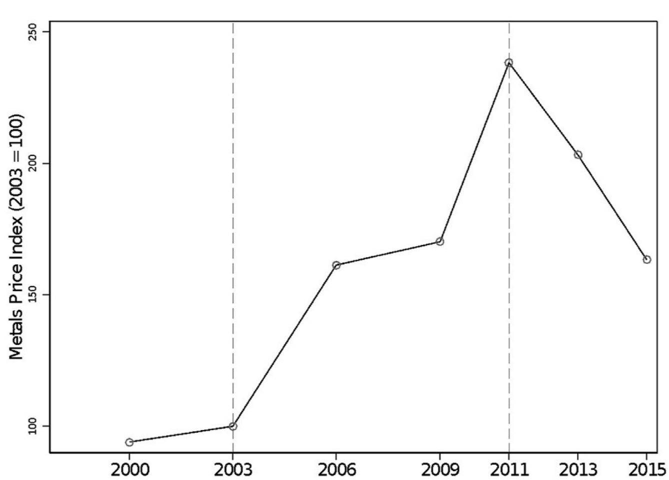


Fig. 2. Metal mining price index dynamic.
Source: Self-elaborated using information from the Chilean Mining Yearbook or "Anuario'' (AMC) provided by the National Geology and Mining Service.
Note: Metal mining price Index is normalized to 2003 values (2003 = 100).

Our empirical strategy is based on a difference-in-difference (DID) methodology in which we focus on the coefficient estimate related to long-run employment defined by the interaction between the metal's price index and being a mining municipality. We use the simultaneous equations approach, defining four different equations to estimate as follows[6]

$$rate\_\ unemployment_{it} = \gamma_0 + \eta_m + \delta_t + \gamma_1 \cdot rate\_school\_enr_{it-l} + \varepsilon_{it} \tag{3.1}$$

$$rate\_school\_enr_{it-l} = \beta_0 + \alpha_m + \mu_t + \beta_1 \cdot schooling\_returns_{it-l} + \beta_2 \cdot rate\_poverty_{\ it-l} + v_{it} \tag{3.2}$$

$$rate\_part\_emp_{it-l} = \pi_0 + \omega_m + \tau_t + \pi_1 \cdot schooling\_returns_{it-l} + \pi_2 \cdot rate\_poverty_{it-l} + u_{it} \tag{3.3}$$

$$schooling\_returns_{it-l} = \gamma_m + \lambda_1 \cdot z_{it} + \lambda_2 \cdot Ln\left[P_{t-l,j}\right] + \lambda_3 \cdot z_{it} \cdot Ln\left[P_{t-l,j}\right] + \lambda_4 \cdot emp\_rate\_dif_{it-l} + \tau_{it} \tag{3.4}$$

6 Our simultaneous equation system is based on the theoretical model performed by Pérez-Trujillo and Rodríguez-Puello (2021).

Where the parameters η_m, α_m, ω_m, and γ_m are regional fixed effects; while δ_t, μ_t, and τ_t are time fixed effects; and γ_0, β_0, and π_0 are constant terms. We use a 3SLS model to estimate the simultaneous equations system in its structural form. This methodology allows us to exploit the correlation of the disturbances across equations since there may be different unobserved elements that jointly affect the error terms in the four equations: ε_{it}, ν_{it}, u_{it}, and τ_{it}, where the subscript i refers to the i^{th} municipality and t to the period considered in the analysis ($t = 2000, 2003, 2006, 2009, 2011, 2013, 2015$ and 2017).

In (3.1) the unemployment rate ($rate\_unemployment_{it}$) depends on the past school enrollment rate ($rate\_school\_enr_{it-l}$), which we lag for 2 periods ($l = 1, 2$). We expect a negative relationship between both variables since the higher the level of enrollment in education, the higher the future employability, and hence the lower the likelihood of being unemployed. Equations (3.2) and (3.3) relate both school enrollment and the labor force participation rate of youth ($rate\_part\_emp_{it-l}$) with schooling returns ($schooling\_returns_{it-l}$)[7] and the rate of poverty ($rate\_poverty_{\,it-l}$),[8] respectively. We expect that schooling returns will have a positive impact on youth enrollment while simultaneously reducing their participation in the labor market, due to a higher wage premium for education (Black et al., 2005). A higher rate of poverty does precisely the opposite since poorer households are more likely to face budget constraints in keeping their children enrolled. The opportunity cost for education is simply too high, and earning a salary may be the only option for maintaining the level of household consumption (Carneiro and Heckman, 2002).

Finally, equation (3.4) uses the DID strategy and defines how schooling returns (the wage premium for education in the labor market) have been affected by the intensity of the MMPSC (by using the log of a metal's price index, $Ln[P_{t-l,j}]$) depending on the municipality's degree of exposure to the shock, which is measured by the mining/not mining (z_{it}) classification previously defined. The wage premium for education is of interest in our analysis since we assume that the salary of low- and medium-low skilled workers increases for the duration of the MMPSC shock (Pellandra, 2015, Pérez-Trujillo and Rodríguez-Puello, 2021). A lower wage premium for education subsequently means fewer incentives for schooling (similar to the evidence found by Black et al. (2005) in their analysis for the US) and lower employability in the long run.

Our interest in estimating (3.4) is the coefficient λ_3, which represents the interaction between the intensity of the MMPSC and being a mining municipality. However, this coefficient does not fully measure the direct effect of the shock on long-run unemployment, school enrollment and youth labor force participation, since its impact in the first stage is on schooling returns and then, in a second stage, on school enrollment and youth labor force participation. In the third and last stage the shock affects long-run unemployment but only as a consequence of the previous stages. Therefore, in the final stage we need to estimate the product of $\lambda_3 \cdot \beta_1 \cdot \gamma_1$ by using a non-linear combination of these estimated coefficients in the model to obtain the effect of the shock on long-run unemployment. Moreover, in equation (3.4) the variable $emp\_rate\_dif_{it-l}$ defines the ratio between the employment rate of high- and low-skilled workers, which is used as a proxy for the likelihood that a high-skilled worker be employed instead of a low-skilled worker.

Furthermore, the estimates of equations (3.2) and (3.3) of the simultaneous equations model are calculated for two different age groups: 15–18 and 18–24. The 15-18 years-old group is not part of the main labor force for mining companies, although these individuals can legally join the labor market. We consider these individuals since they belong to the least educated group in the labor force population and are therefore the most vulnerable post-shock. According to Pérez-Trujillo and Rodríguez-Puello (2021), these individuals dropped out of school to participate in the labor market during the MMPSC in Chile, particularly in those municipalities more exposed to the shock, i.e., metal mining municipalities. These individuals were employed in sectors that existed as a result of the increased internal demand from the MMPSC shock e.g., construction, retail trade and other services (see Appendix, Figure A1 (a)) (Rehner and Vergara, 2014). The end of the MMPSC shock meant that the labor demand in these industries decreased, particularly in said metal mining municipalities (see Appendix, Figure A1 (b) and Figure A2 (b)),[9] thus destroying an important part of the jobs created during the shock. This directly impacted said dropouts, who for lack of an education, now had a lower chance of finding a new job in a different industry.

Furthermore, according to the literature it is important to differentiate by age ranges since they can capture differences in the vulnerability of labor and education to shocks (Zimmermann, 2020).[10] We expect the MMPSC shock to have negatively impacted youth enrollment since the wage premium for schooling decreased during the shock (contrasted by equation (3.2)), whereas at the same time these individuals increased their participation in the labor market (contrasted by equation (3.3)).

Finally, it is important to recognize that the sampling carried out by the CASEN for municipalities with a small population size might not be representative of the selected variables in the analysis and could therefore introduce bias into the estimates (Modrego and Berdegué, 2015). The smaller the population size of the municipality, the greater the measurement error bias, causing the results to converge in probability to a value close to 0 (Greene, 2012). When the measurement error is in the variables, a common correction is the use of instrumental variables. Nevertheless, this is not possible in our case since the source of measurement error is in the sample itself, and any instrumental variable used as a correction would have this error (Angrist and Krueger, 2001).

Our estimates require controlling for this potential source of measurement error bias. To solve this potential source of endogeneity, we follow Pérez-Trujillo and Rodríguez-Puello (2021) and use three different estimates of the simultaneous equations model in terms of the population size of the municipalities considered in the study: (a) using the whole available sample, (b) considering only those municipalities with at least 25,000 inhabitants and (c) considering only those municipalities with at least 50,000 inhabitants. The greater the population size of the analyzed observable units, the more stable the estimated

[7] We estimate the following Mincerian wage equation for each municipality, using the information available in CASEN (for every CASEN between 2000 and 2017) for all workers in a municipality, correcting for sample selection bias: $\ln w_{i,v} = \alpha_0 + \alpha_1 \cdot Year_School_{i,v} + \alpha_2 \cdot Age_{i,v} + \alpha_3 \cdot Age^2_{i,v} + \alpha_4 \cdot Gender_{i,v} + \theta_{h,v} + \lambda_{i,v} + u_{i,v}$$i$ being each worker over 15 years old that is a resident in a municipality v. The estimate includes years of schooling ($Year\_School_{i,v}$), age ($Age_{i,v}$) and its square, gender ($Gender_{i,v}$), the h^{th} economic sector in which the worker participates ($\theta_{h,v}$) and the Mills inverse ratio associated with the probability of being employed in the municipality ($\lambda_{i,v}$). To calculate the latter, we apply a probit model to identify the probability of being employed. This probit model considers the following regressors: years of schooling, age and its quadratic mean, gender, and the number of people per household. Finally, we obtain the estimated value of coefficient α_1, which will be identified as the proxy for schooling returns (Pérez-Trujillo and Rodríguez-Puello, 2021).

[8] This measure is based on the definition of a minimum income level for an acceptable level of household consumption.

[9] Employment in construction, retail, trade and other services decreased nearly 55–63% between 2000 and 2017 in metal mining municipalities (Appendix, Figure A1 (b)).

[10] Although secondary education for individuals between 15 and 18 years old is mandatory (Ley N°19.876), in Chile a 15-year-old can legally work. It is common for youth in less developed countries to drop out of school to join the labor force due to the social and economic conditions of their households (Carneiro and Heckman, 2002).

coefficients are, reducing the impact of the measurement error bias.[11]

4. Descriptive evidence

In the following section we analyze whether the MMPSC shock impacted the unemployment rate while it lasted and after it ended. We compare the behavior of mining and non-mining municipalities using both the weighted employment and AMC exposure measures proposed, since we expect the former to be more affected by the shock. Table 1 shows the main descriptive statistics (mean and standard deviation) of the unemployment rate, labor participation rate and school enrollment of young people for the age groups of 15–18 years and 18–24 years, as well as, the estimated returns to schooling for each municipality. The table divides the information into three different periods:

(i) year 2000, prior to the MMPSC,
(ii) the period between 2003 and 2011, when the MMPSC occurs, and
(iii) the period between 2013 and 2017, when the MMPSC ends.

The aim here is to compare the behavior of each variable considered in said periods. Likewise, the municipalities are differentiated between mining and non-mining using the two classifications proposed: (a) Álvarez et al. (2021), mining municipalities are those located in the fourth quartile based on the weight of the metal mining sector over total employment in the year 2000, and (b) AMC. The results shown regarding the unemployment rate indicate that both types of municipalities had an unemployment rate of approximately 10% in 2000, with an abrupt reduction in said rate during the MMPSC period, particularly for the mining municipalities (a 2.5 percentage point reduction considering AMC criteria). However, it is only in these territories where there is an increase in the unemployment rate after the end of the shock (2013–2017).

Regarding the school enrollment rate, we observe that mining municipalities have a higher level of school attendance than non-mining municipalities prior to the start of the shock (year 2000). However, during the MMPSC the growth rate in school enrollment was lower in mining municipalities, both for young people between 15 and 18 years old and between 18 and 24 years old. The decrease in returns to schooling during the shock is a clear factor and is reflected in the lower rates within mining municipalities.

Finally, the labor participation rate of young people increased between 1 and 2 percentage points during the MMPSC, particularly for the 18–24 years old segment within mining municipalities. The employment and income opportunities offered by the super cycle could have been a significant incentive to this group.

In addition, it should be noted that even though the MMPSC started in 2003, its impact on school attendance wasn't felt until years later. As the shock persists over time the perception of it being transitory becomes blurred, conditioning agents to react as if it were a permanent or long-term phenomenon. The longer the shock persists, the greater the (negative) effect on the young and their incentives to remain in school (Black et al., 2005). Table 2 shows the mean school enrollment rate divided by age group and municipality type (mining and non-mining). For the year 2009 (six years into the MMPSC), the mining municipality school enrollment for the youngest age group was 3.5 percentage points below what was observed in 2003, and similar to the rate in 2000. Enrollment began to accelerate again in 2011, a trend that continued until 2017. Meanwhile, in non-mining municipalities the rate in 2009 was only 1 percentage point below that observed in 2003, and 4 percentage points above the rate in 2000.

Likewise, when considering the measure of Álvarez et al. (2021), the growth rate for school enrollment in mining municipalities is lower for individuals between 15 and 18 years old between 2000 (80.1) and 2009 (81.9) than that in non-mining municipalities (76.6 in 2000 and 80.6 in 2009). Finally, in 2017 both types of municipalities have enrollment rates of approximately 90%.

This dynamic is not observed for the 18–24 years old segment, who have increased their school enrollment almost steadily since 2000 in both mining and non-mining municipalities. This might indicate that it is the youngest age group that shows the greatest disruption in schooling during the MMPSC, particularly in the municipalities most exposed to the shock i.e., the mining ones.

Fig. 3 show the dynamics of the average unemployment rate for both groups of municipalities during and after the expansion phase of the shock. It is important to highlight that the average unemployment rate for mining municipalities is lower during expansion (2003–2011), however both groups do see a rate decrease. This can be observed in panels (a.1) and (a.2) of Fig. 3. Nevertheless, a change in this trend occurs when expansion ends; the unemployment rate of mining municipalities begin to rise after 2011 and then surpasses that of non-mining municipalities (which see stagnant rates).

When we differentiate the analysis between high-skilled, panels (c.1) and (c.2), and low-skilled workers, panels (b.1) and (b.2),[12] we can observe the negative effect of the shock on low-skilled workers. Remarkably, there is no discernible trend or behavior for high-skilled workers. In line with Pérez-Trujillo and Rodríguez-Puello (2021), the incentives for schooling during the shock were lower due to a reduction in the wage premium for education in the labor market and the better employment opportunities for low-skilled workers. However, dropouts from during the expansion phase later lost their jobs, with unemployment for low-skilled workers increasing since 2011, particularly in mining municipalities.

The analysis in Fig. 3 is complemented with a Difference-in-Difference strategy which identifies whether the differences in the unemployment rates ($rate\_unemployment_{it}$) of mining and non-mining municipalities are statistically different after the year 2011 (when the expansion phase of the MMPSC ended). To do so, we estimate the following equation by OLS:

$$rate\_unemployment_{it} = \beta_0 + D_t + z_{it} + D_t \cdot z_{it} + v_{it} \tag{4}$$

Where D_t is a dummy with a value of 1 for the years after the shock (2013, 2015, and 2017) and 0 otherwise, while z_{it} is a regressor which differentiates mining and non-mining municipalities using the two measures defined above. Table 3 includes the estimates of the interaction between $D_t \cdot z_{it}$. These show a positive and significant effect for the end of the MMPSC shock on the unemployment rate, being higher for mining municipalities (for both the Álvarez et al. (2021) and AMC criterion). Furthermore, this effect is only observed when both the total and low-skilled unemployment rates are considered. We do not find a discernible impact on the unemployment rate of high-skilled workers. These results are in line with the dynamics observed in Fig. 3, in that low-skilled workers saw a negative impact on their employability at the end of the shock.

5. Results

Tables 4 and 5 present the main results of the estimates of the simultaneous equations system. We performed a different analysis for both the 15-18- and 18-24-years old group of individuals when considering the estimates of equations (3.2) and (3).3). In order to

[11] The elimination from the estimates of municipalities with small populations will produce results that can only be valid for the sample under consideration. However, other authors including Card (2001) have applied similar distinctions in their applied studies.

[12] A high-skilled worker is classified as someone who has completed tertiary education (either university or technical). Low-skilled workers are those that have completed at most a high school education.

reduce the measurement error bias, these estimates divide the sample of municipalities into three different groups depending on the level of population. When we consider the outcomes obtained for the interaction of interest ($\lambda_3 \cdot \beta_1 \cdot \gamma_1$), the results show that being a mining municipality during the MMPSC shock positively and significantly impacted future unemployment (see Table 5). These outcomes are stable regardless of the measure used to classify the municipalities (into mining and non-mining) or the age group considered.

These estimates also show that the shock had a negative and statistically significant impact on schooling returns, particularly in mining municipalities, decreasing the wage premium for education.[13] Since the decrease in schooling returns positively affects the early labor force participation (and negatively affects schooling decisions), it is possible to extrapolate that the shock also indirectly impacted both elements. As the MMPSC shock raised the ratio of dropouts in mining municipalities during expansion, the future employability of these individuals decreased, especially after the shock ended. Furthermore, the coefficients estimated for the interaction of interest increase their significance when the population size is higher, as these estimates reduce the effect of measurement error bias and are therefore more reliable.

We have also performed additional estimates (similar to the above), but we add an additional lagged period for the following variables: $Ln[P_{t-2,j}]$, $emp\_rate\_dif_{it-2}$, $rate\_poverty_{\ it-2}$, $schooling\_returns_{it-2}$, $rate\_part\_emp_{it-2}$, and $rate\_school\_enr_{it-2}$. We expect the long-term unemployment of mining municipalities to be more impacted by the end of the shock. Table 6 shows the estimates for the interaction of interest ($\lambda_3 \cdot \beta_1 \cdot \gamma_1$) which we differentiate by the mining municipality classification and the age group considered in equations (3.2) and (3).3). The results for the 15–18 years old age group indicate that the MMPSC shock played a significant role in the schooling enrollment of youth, with a higher than previously estimated impact (see Table 4) on the long term unemployment rate of the municipality, ultimately lagging by two periods.

The estimates for (3.2) and (3.3) consider individuals between 18 and 24 years old, and these coefficients are lower than those shown in Table 5, providing evidence for a smaller effect on long-run unemployment.

We have performed new estimates differentiating the unemployment rate for high-skilled and low-skilled workers due to the analysis in Table 3, which identifies a different response in the unemployment rate for both groups. We expect a negative impact to be primarily concentrated on low-skilled workers due to their employability at the end of the MMPSC shock. We also divide the estimates by age group, the two criterion for classifying the mining municipalities, two lags for the following variables: $Ln[P_{t-.j}]$, $emp\_rate\_dif_{it-.}$, $rate\_poverty_{\ it-.}$, $schooling\_returns_{it-.}$, $rate\_part\_emp_{it-.}$, and $rate\_school\_enr_{it-.}$, and the population size (in order to correct for the potential measurement error in the regressors).

In Fig. 4 we show the estimates of the non-linear combination for the interaction of interest ($\lambda_3 \cdot \beta_1 \cdot \gamma_1$), which measures the impact of the shock on the unemployment rate. The coefficient associated with said interaction is positive and statistically significant for those individuals that are low-skilled workers, whereas for the high-skilled this effect includes a negative coefficient that is statistically significant under the AMC criterion for classifying mining municipalities. This evidence therefore confirms that the effect of the MMPSC shock was particularly focused on those low-skilled workers living in areas more exposed to the shock i.e., mining municipalities.

Furthermore, this effect is higher when we consider those individuals between 15 and 18 years old that abandon schooling during the shock, as compared to those between 18 and 24. It is likely that the latter group has a lower level of education and therefore a lower level of employability and less chances to maintain their job (or find a new one) at the end of the MMPSC shock, all of which contributes to an increase in unemployment in the long run. Moreover, the results show that the effect of the shock is higher at the latest point in the period considered, highlighting the negative impact of the shock on future unemployment and the inefficiency of the labor market.[14]

6. Conclusions

The aim of this paper is to estimate the effect of a commodity shock on long-run unemployment. We analyze the case of Chile during the MMPSC, a shock that lasted around a decade, significantly disrupting its economy and labor market. We find evidence that this shock negatively impacted the wage premium for education. Our results are consistent with Pellandra (2015) in that the shock increased the demand for low and medium-low skilled workers, increasing both job opportunities and

[13] Due to the increased migration to Chile during the last 15 years, we decided to perform new estimates for the simultaneous equations system proposed, including the lag of the foreign-born share of the labor force ($p_{it-1} = M_{it-1}/A_{it-1}$*100) as an additional regressor in equations (3.1), (3.2) and (3.3). Where M_{it-1} represents the number of migrants participating in the labor force in the *ith* municipality at period $t-1$, and A_{it-1} the total labor force. The data comes from the Chilean National Socioeconomic Characterization Survey (CASEN) 2006, 2009, 2011, 2013, 2015, and 2017, (data was not available for CASEN 2000 and 2003). This additional regressor included in our estimates allows us to control for the effect of migration in our estimates, avoiding the potential existence of omitted variable bias. The new regressor is lagged in equations (3.1), (3.2) and (3.3) of the manuscript since migration could have an impact on the unemployment rate, affecting the labor market equilibrium (Borjas, 2003), and reducing the participation of youth in the labor market (i.e., dropouts), since these new entrants to the market might replace young workers. In 2015 the 75% of migrants (calculus with CASEN 2015) were employed in construction, wholesale and retail trade, and services, directly competing with young workers. This increased competition means fewer incentives to drop out, resulting in a lower youth labor participation (Altonji and Card, 1991). The outcomes obtained show that p_{it-1} is not significant in the estimates shown in Tables 2 and 3 Therefore, we do not have empirical evidence to demonstrate that migration has had a relevant effect on unemployment during the period considered. However, it is important to note that the CASEN survey does not provide specific information about migration or the behavior of the phenomenon, but rather it provides an understanding of the situation of households and the population, particularly in terms of poverty, as well as the impact of social policy. Therefore, the data used to calculate (p_{it-1}) might suffer from measurement error, biasing the new estimates performed (Contreras et al., 2012). These new estimates are available to the reader, upon request to the authors.

[14] We should acknowledge that a significant percentage of the workers in the mining industry live outside the local labor market (Hernández et al., 2022). This long-distance commuting could therefore distort the labor market analysis, especially in mining regions. Despite the importance of this phenomenon, Chile has no available data on commuting at either the municipal or regional level. Therefore, we are not able to incorporate long-distance commuting patterns in our analysis. One possible alternative is to use functional regions (instead of municipalities). Functional regions (FR) were constructed as socially constructed spaces in Chile and are bounded by actual flows of resources (e.g., workers, goods, and information) across contiguous administrative borders (Berdegué et al., 2019; Karlsson et al., 2010). However, using FR does not fully address the mining regions growing dependence on long-distance commuting (Atienza, 2021). On the one hand, FR describe the spatial unit whose local features define the economic system, focusing on commuters living in contiguous municipalities that conform a FR. People who belong to the same FR both live and work there. On the other hand, long-distance commuting refers to people who use shift systems and live and work in different, usually distant, and non-contiguous, municipalities. Therefore, long-distance commuters often work in one functional region but live in another one. In summary, there is no correlation between the definition of FR (commuters living in contiguous municipalities within a FR) and long-distance commuting (long distance-commuters who do not live in the same functional region where they work). However, as an attempt to address commuting patterns in our assessment, we performed our estimations using FR as our unit of analysis. As expected, (based on our recent discussion), we do not find any significant effect in our main variables of interest. These results are available upon request to the authors.

Table 1
Mean and standard deviation for the main variables considered in the analysis, dividing the sample by period and group of municipality according to the mining/non-mining classification.

Variable	Álvarez et al. (2021)						AMC					
	2000		2003–2011		2013–2017		2000		2003–2011		2013–2017	
	Metal	Non-Metal	Metal	Non-Metal	Metal	Non-Metal	Metal	Non-Metal	Metal	Non-Metal	Metal	Non-Metal
Unemployment rate ($rate\_unemployment_{it}$).	9.66 (3.39)	9.86 (4.46)	7.69 (3.46)	8.59 (4.28)	8.32 (4.14)	7.83 (4.26)	9.94 (3.71)	9.79 (4.31)	7.50 (3.29)	8.54 (4.24)	8.15 (4.34)	7.91 (4.22)
School enrollment rate for youth between 15 and 18 years old ($rate\_school\_enr_{it}$).	80.10 (8.37)	76.67 (8.13)	82.77 (7.97)	81.76 (8.57)	85.69 (9.53)	85.95 (10.22)	79.98 (7.66)	77.09 (8.36)	82.63 (8.57)	81.87 (8.43)	86.52 (9.16)	85.79 (10.21)
School enrollment rate for youth between 18 and 24 years old ($rate\_school\_enr_{it}$).	31.08 (12.17)	28.09 (9.63)	33.88 (13.41)	33.73 (11.87)	38.61 (14.16)	40.97 (14.26)	30.01 (9.58)	28.62 (10.52)	32.59 (11.53)	33.96 (12.33)	38.40 (13.60)	40.78 (14.36)
Computed by applying a Mincerian wage equation ($schooling\_returns_{it}$).	8.42 (4.85)	8.45 (5.29)	6.94 (5.25)	7.43 (6.40)	8.28 (6.74)	7.73 (5.98)	8.10 (4.58)	8.86 (5.28)	7.02 (5.17)	7.37 (6.32)	7.70 (6.48)	7.89 (6.12)
Employment participation rate for youth between 15 and 18 years old ($rate\_part\_emp_{it}$).	12.09 (6.27)	12.57 (6.06)	10.50 (6.20)	11.48 (7.27)	9.08 (8.06)	10.40 (8.23)	12.07 (6.24)	12.51 (6.09)	10.55 (6.96)	11.38 (7.07)	7.71 (6.64)	10.50 (8.38)
Employment participation rate for youth between 18 and 24 years old ($rate\_part\_emp_{it}$).	47.64 (10.21)	48.43 (8.29)	49.17 (9.69)	49.98 (9.86)	46.78 (12.41)	46.77 (11.62)	46.39 (10.13)	48.57 (8.51)	47.30 (10.33)	48.84 (9.87)	44.59 (11.55)	47.30 (10.33)

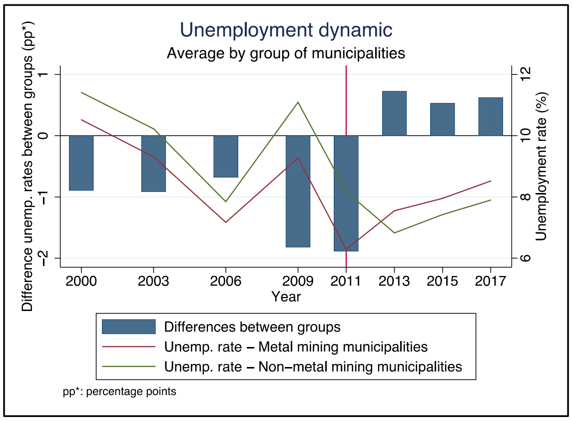
Source: Self-elaborated with CASEN 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017.
Note: Álvarez et al. (2021) consider mining municipalities located in the fourth quartile based on the weight of the metal mining sector over total employment in the year 2000. The variable $schooling\_returns_{it}$ is a measure for the percentage increase in hourly wage experienced by each worker for each additional year of study.

Table 2
Mean of schooling enrollment rate, dividing the sample by period and group of municipalities according to the mining/non-mining classification.

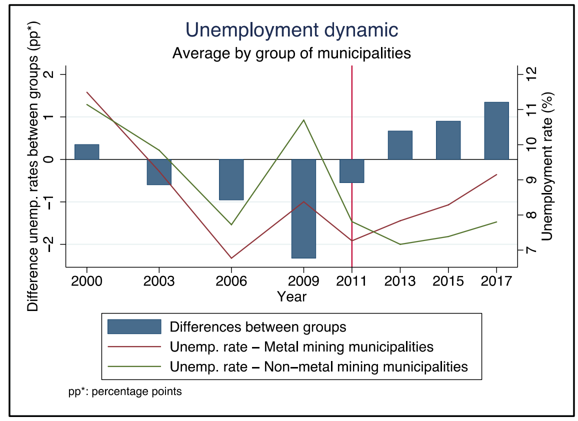
Year	Álvarez et al. (2021)				AMC			
	15 to 18		18 to 24		15 to 18		18 to 24	
	Mining	Non-Mining	Mining	Non-Mining	Mining	Non-Mining	Mining	Non-Mining
2000	80.10	76.68	31.08	28.09	79.98	77.09	30.01	28.62
2003	82.80	82.06	31.62	31.20	83.20	82.06	31.39	31.28
2006	82.83	81.06	31.41	31.20	83.12	81.17	30.58	31.35
2009	81.97	80.65	34.82	33.87	79.67	81.15	32.99	34.26
2011	83.48	83.30	37.65	38.43	84.56	83.14	35.35	38.75
2013	86.31	86.60	40.53	42.17	86.39	86.57	39.53	42.20
2015	87.92	89.46	40.63	46.07	88.71	89.19	41.11	45.52
2017	88.44	89.56	42.20	45.42	90.61	89.10	42.39	45.11

Source: Self-elaborated with CASEN 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017.
Note: Álvarez et al. (2021) considers mining municipalities to be those located in the fourth quartile based on the weight of the metal mining sector over total employment in the year 2009.

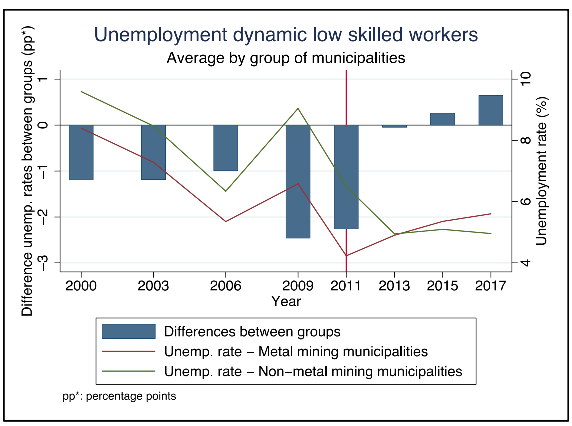
Weighted employment measure (Álvarez et al., 2021) AMC measure



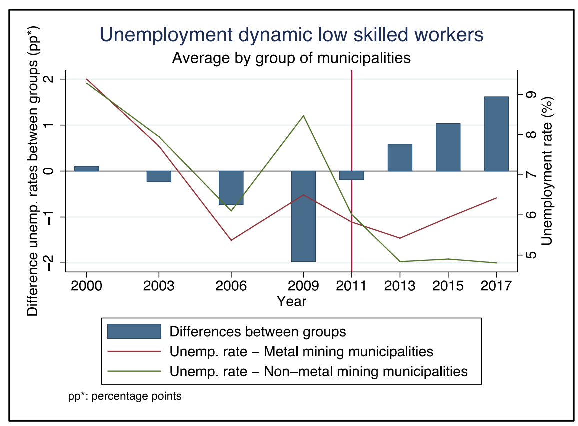
(a.1) Average Unemployment rate



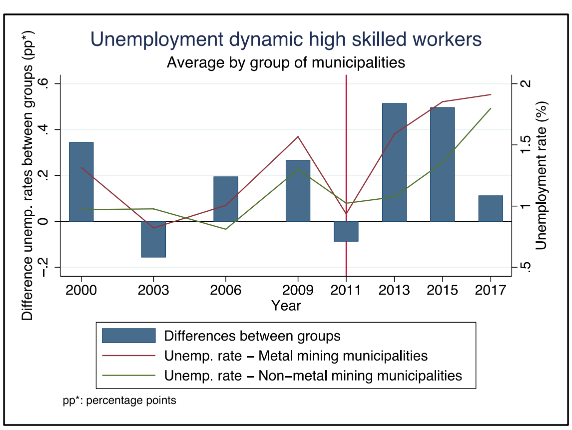
(a.2) Average Unemployment rate



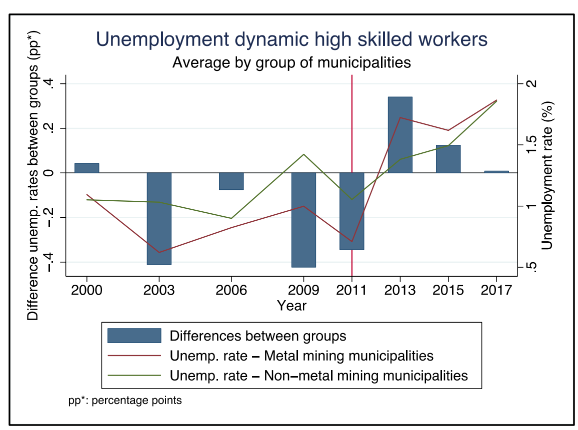
(b.1) Average Unemployment rate for low-skilled workers



(b.2) Average Unemployment rate for low-skilled workers



(c.1) Average Unemployment rate for high-skilled workers



(c.2) Average Unemployment rate for high-skilled workers

Fig. 3. Unemployment rate dynamics for mining and non-mining municipalities, using the two measures for both categories, for the period 2000–2017.
Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017.
[a] The red line defines the year in which the expansion phase of the MMPSC ended. 2013–2017 is the period after the shock.

Table 3
DID estimates dividing the analysis by skill-level.

Estimates for: $D_t \cdot z_{it}$	Weighted employment measure (Álvarez et al., 2021)		AMC measure	
Unempl. Rate Total	0.0800 (0.0295)	***	1.0128 (0.0475)	**
Unempl. Rate (Low-skilled)	0.0873 (0.0272)	***	1.0733 (0.4294)	**
Unempl. Rate (High-skilled)	0.0010 (0.0067)		0.0580 (0.1168)	

Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: *: Statistically significant at the 0.10 level, **: at the 0.05 level, ***: at the 0.01 level.

wages, particularly in the areas more exposed to the shock, i.e., mining municipalities. As a consequence of this decrease in the wage premium for education, we also provide empirical evidence of a simultaneous decrease in school enrollment rates and an increase in the labor force participation of the 15-18-year age group in mining municipalities during the shock (similarly to Pérez-Trujillo and Rodríguez-Puello (2021)). In the long term, this negatively impacted the employability of these individuals, increasing their likelihood of unemployment once the MMPSC shock ended.

These results contribute to understanding how a commodity shock conditions an economic equilibrium not only while it lasts, but long after. The MMPSC shock was a negative driver in the accumulation of human capital in the most exposed areas, limiting future economic growth and increasing unemployment after the shock ended. A shock will inevitably come to an end; therefore, policy makers must look past the short-term positive effects in order to appreciate its long-term economic disruption. Policies and measures aimed at the stability of labor market conditions, economic shock preparedness and government response capacities are key.

Finally, it is important to note that the effects of long shock cycles (such as the decade-long one analyzed here), are directly influenced by the agents' expectations. For example, a shock that appears to be long-term or even permanent will influence an individual's decision to drop out of school in order to take advantage of the low-skilled labor demand and high wages, significantly disrupting the labor market (Black et al., 2005). Considering that metal mining prices tend to be cyclical (Radetzki et al., 2008; Tilton, 2006; Kabwe and Yiming, 2015), the length of the overall shock and of its phases (expansion and contraction) matters. In the case of the MMPSC, prices increased around 67% from 2003 to 2011 and then dropped around 13% from 2011 to 2015.[15] Such a change in prices marks the end of a cycle, and it also influences agents' expectations about the economy and the labor market, an effect that is demonstrated in our results. Even if prices were to increase again, as has been the case in 2021 and the first half of 2022, we do not have enough evidence (yet) to fully understand the impact. Furthermore, at this point in time the CASEN does not yet have data on unemployment to explore the effect of the 2021–2022 copper prices. A sustained increase in the prices of raw materials like copper would present an opportunity for

Table 4
3SLS estimates for 15–18 years old individuals, using the two criterions considered to identify the mining municipalities.

	(1) Weighted employment measure (Álvarez et al., 2021)						*(2) AMC measure*					
Population	Whole sample		($\geq 25,000$)		($\geq 50,000$)		Whole sample		($\geq 25,000$)		($\geq 50,000$)	
Estimates of equation (3.1): $rate\_unemployment_{it}$												
$rate\_school\_enr_{it-1}$ (coefficient estimated γ_1)	−0.1470	***	−0.1889	***	−0.1506	***	−0.1310	***	−0.1611	***	−0.1360	***
	(0.0525)		(0.0470)		(0.0433)		(0.0498)		(0.0408)		(0.0370)	
γ_0	17.8390	***	23.0622	***	19.6572	***	16.7967	***	20.8988	***	18.6940	***
	(4.7164)		(4.3816)		(3.9635)		(4.4482)		(3.6589)		(3.2700)	
Estimates of equation (3.2): $rate\_school\_enr_{it-1}$												
$schooling\_returns_{it-1}$ (coefficient estimated: β_1)	1.0962	***	0.7839	***	1.2274	***	1.3217	***	0.9382	***	1.0218	***
	(0.2424)		(0.2592)		(0.3840)		(0.2648)		(0.2449)		(0.2886)	
$rate\_poverty_{it-1}$ (coefficient estimated: β_2)	−0.1555	***	−0.3116	***	−0.3483	***	−0.1460	***	−0.3487	***	−0.4403	***
	(0.0413)		(0.0632)		(0.0944)		(0.0428)		(0.0644)		(0.0885)	
β_0	84.0562	***	87.7420	***	81.2723	***	81.3077	***	82.5496	***	88.6612	***
	(3.1449)		(4.6426)		(6.0748)		(3.4335)		(3.8306)		(4.2823)	
Estimates of equation (3.3): $rate\_part\_emp_{it-1}$												
$schooling\_returns_{it-1}$ (coefficient estimated: π_1)	−0.6033	***	−0.5000	***	−0.5882	**	−0.5923	***	−0.2848	*	−0.3533	*
	(0.1790)		(0.1933)		(0.2555)		(0.1850)		(0.1677)		(0.1928)	
$rate\_poverty_{it-1}$ (coefficient estimated: π_2)	0.0051		0.0270		0.0518		0.0041		0.0636		0.0986	
	(0.0354)		(0.0519)		(0.0725)		(0.0362)		(0.0516)		(0.0697)	
π_0	10.1842	***	7.0076	**	8.8790	**	10.6672	***	7.7499	***	8.3845	***
	(2.4571)		(3.4769)		(4.0705)		(2.4473)		(2.6638)		(2.9131)	
Estimates of equation (3.4): $schooling\_returns_{it}$												
$z_{it=0}$	0.4952	***	0.7391	***	0.9191	***	8.3717	***	14.5283	***	17.8110	***
	(0.1467)		(0.2592)		(0.2621)		(1.9220)		(3.2309)		(3.5858)	
$Ln[P_{t-1,j}]$	0.7610	***	0.6984	**	1.0952	***	1.0456	***	1.3609	***	1.5521	***
	(0.1910)		(0.3404)		(0.3312)		(0.1809)		(0.2796)		(0.2623)	
$emp\_rate\_dif_{it-1}$	0.0344	***	0.0292	***	0.0214	***	0.0192	***	0.0178	***	0.0153	***
	(0.0043)		(0.0039)		(0.0038)		(0.0026)		(0.0022)		(0.0021)	
$z_{it=0} \cdot Ln[P_{t-1,j}]$ (coefficient estimated: λ_3)	−0.0720	***	−0.1015	**	−0.1449	***	−1.5369	***	−2.6090	**	−3.3314	***
	(0.0266)		(0.0460)		(0.0456)		(0.3678)		(0.6273)		(0.6909)	
Observations	1790		876		544		1988		911		571	
Interactions $\lambda_3 \cdot \beta_1 \cdot \gamma_1$	0.0116	*	0.0150	*	0.0268	**	0.2662	**	0.3943	**	0.4631	**
	(0.0062)		(0.0089)		(0.0131)		(0.1246)		(0.1615)		(0.1895)	

Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: *: Statistically significant at the 0.10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (3.1), (3.2) and (3.3) include both regional and time fixed effects in their estimates. Meanwhile, (3.4) only incorporates regional fixed effects.

[15] Author's own calculation based on data from the Mining Yearbook provided by SERNAGEOMIN.

Table 5
3SLS estimates for 18–24 years old individuals, using the two criterions considered to identify the mining municipalities.

	(1) Weighted employment measure (Álvarez et al., 2021)						(2) AMC measure					
Population	Whole sample		($\geq 25,000$)		($\geq 50,000$)		Whole sample		($\geq 25,000$)		($\geq 50,000$)	
Estimates of equation (3.1): *rate_ unemployment*$_{it}$												
rate_school_enr$_{it-1}$ (coefficient estimated γ_1)	−0.0401	***	−0.0546	***	−0.0458	***	−0.0429	***	−0.0523	***	−0.0418	***
	(0.0163)		(0.0148)		(0.0132)		(0.0160)		(0.0139)		(0.0122)	
γ_0	6.4503	***	9.0151	***	8.6139	***	6.9546	***	9.1976	***	8.7558	***
	(0.9987)		(1.3848)		(1.1672)		(0.9347)		(1.0570)		(0.9059)	
Estimates of equation (3.2): *rate_school_enr*$_{it-1}$												
schooling_returns$_{it-1}$ (coefficient estimated: β_1)	3.9648	***	3.3778	***	4.4460	***	4.5792	***	3.3044	***	3.4096	***
	(0.5596)		(0.6522)		(1.0709)		(0.6107)		(0.5723)		(0.6706)	
rate_poverty $_{it-1}$ (coefficient estimated: β_2)	−0.3033	***	−0.6198	***	−0.9406	***	−0.3417	***	−0.7763	***	−1.1783	***
	(0.0623)		(0.1150)		(0.1910)		(0.0703)		(0.1183)		(0.1642)	
β_0	26.8394	***	42.2809	***	27.2688	*	18.4445	**	26.7341	***	23.3752	***
	(7.0265)		(10.6113)		(16.4102)		(7.6992)		(8.5511)		(9.6764)	
Estimates of equation (3.3): *rate_part_emp*$_{it-1}$												
schooling_returns$_{it-1}$ (coefficient estimated: π_1)	−2.1243	***	−1.8628	***	−2.4311	***	−2.5156	***	−1.7746	***	−2.0307	***
	(0.3495)		(0.4193)		(0.6576)		(0.3839)		(0.3709)		(0.4670)	
rate_poverty $_{it-1}$ (coefficient estimated: π_2)	−0.1250	**	0.0714		0.2680	**	−0.0957	*	0.1861	**	0.4097	***
	(0.0519)		(0.0858)		(0.1361)		(0.0555)		(0.0882)		(0.1285)	
π_0	54.9515	***	44.6035	***	52.5788	***	60.1534	***	55.5371	***	56.5295	***
	(4.5279)		(6.9950)		(10.1622)		(4.9121)		(5.6331)		(6.8099)	
Estimates of equation (3.4): *schooling_returns*$_{it}$												
$z_{it=0}$	0.3525	***	0.5120	***	0.4847	***	6.0546	***	10.9502	***	10.3136	***
	(0.0921)		(0.1712)		(0.1748)		(1.2406)		(2.3125)		(2.6627)	
$Ln[P_{t-1,j}]$	0.5870	***	0.5075	*	0.9932	***	0.8475	***	1.2419	***	1.4379	***
	(0.1705)		(0.3076)		(0.3083)		(0.1671)		(0.2722)		(0.2586)	
emp_rate_dif$_{it-1}$	0.0370	***	0.0323	***	0.0226	***	0.0184	***	0.0192	***	0.0161	***
	(0.0043)		(0.0037)		(0.0037)		(0.0026)		(0.0021)		(0.0021)	
$z_{it=0} \cdot Ln[P_{t-1,j}]$ (coefficient estimated: λ_3)	−0.0606	***	−0.0766	**	−0.0811	***	−1.1086	***	−2.0233	**	−1.9204	***
	(0.0167)		(0.0300)		(0.0299)		(0.2377)		(0.4457)		(0.5060)	
ObservationsInteractions $\lambda_3 \cdot \beta_1 \cdot \gamma_1$	1790		876		544		1988		911		571	
	0.0096	*	0.0141	*	0.0165	**	0.2181	**	0.3501	***	0.2740	**
	(0.0049)		(0.0073)		(0.0081)		(0.0996)		(0.1316)		(0.1142)	

Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: *: Statistically significant at the 0.10 level, **: at the 0.05 level, ***: at the 0.01 level. Equations (3.1), (3.2) and (3.3) include both regional and time fixed effects in their estimates. Meanwhile, (3.4) only incorporates regional fixed effects..

Table 6
3SLS estimates of the interactions $\lambda_3 \cdot \beta_1 \cdot \gamma_1$.

Interactions $\lambda_3 \cdot \beta_1 \cdot \gamma_1$	(1) Weighted employment measure (Álvarez et al., 2021(2) 8)						(2) AMC measure					
Population	Whole sample		($\geq 25,000$)		($\geq 50,000$)		Whole sample		($\geq 25,000$)		($\geq 50,000$)	
15-18 age group	0.0133 (0.0071)	*	0.0151 (0.0098)		0.0297 (0.0147)	**	0.3748 (0.1584)	**	0.4405 (0.1837)	**	0.5510 (0.2271)	**
18-24 age group	0.0076 (0.0049)		0.0123 (0.0076)		0.0154 (0.0085)	*	0.1937 (0.1035)	*	0.2983 (0.1223)	**	0.2496 (0.1152)	**

Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: *: Statistically significant at the 0.10 level, **: at the 0.05 level, ***: at the 0.01 level. The table shows 3SLS estimates of the interactions $\lambda_3 \cdot \beta_1 \cdot \gamma_1$, considering a second lagged period in the analysis for: $Ln[P_{t-2,j}]$, *emp_rate_dif*$_{it-2}$, *rate_poverty* $_{it-2}$, *schooling_returns*$_{it-2}$, *rate_part_emp*$_{it-2}$ and *rate_school_enr*$_{it-2}$, using the two criterions considered to identify the mining municipalities.
Each different age group is considered for the estimates of equations (3.2) and (3.3) of the simultaneous equations system.

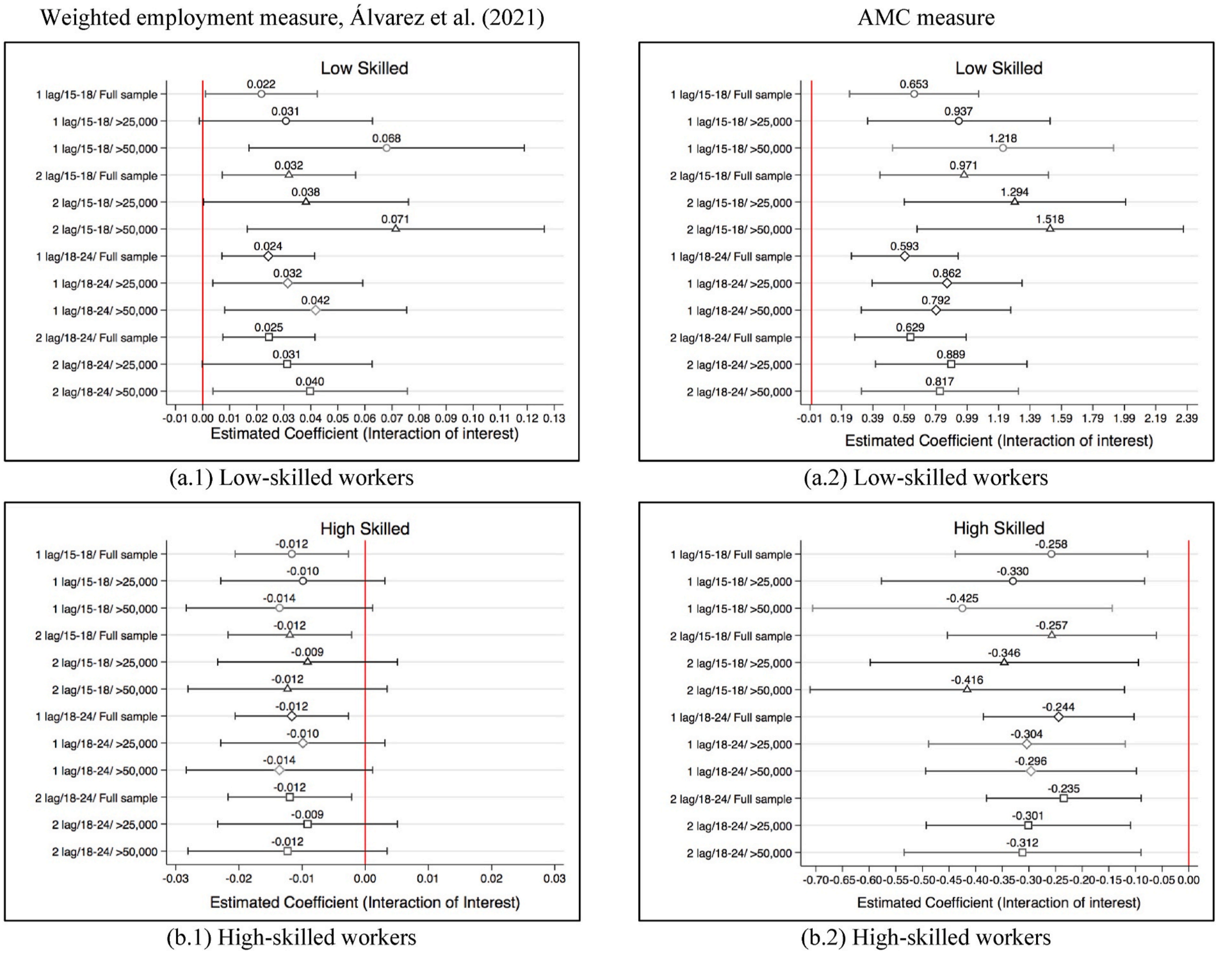


Fig. 4. Estimates of the non-linear combination for the interaction of interest ($\lambda_3 \cdot \beta_1 \cdot \gamma_1$) differentiating the analysis via different combinations of the mining municipality classification, the period in which the MMPSC shock ended, the age group, and the population size.
Source: Self-elaborated using CASEN database for the period 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. [a] Red line defines the zero value. Each different age group is considered for the estimates of equations (3.2) and (3.3) of the simultaneous equations system.

further research, and this analysis would be an appropriate paper to expand on in order to grasp long term trends.

Author contributions

Gabriel Rodríguez Puello has participated in the following stages of the research: Conceptualization, Methdology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing-Original Manuscript, Visualization, and Project Administration. **Alicia Chávez** has participated in the following stages of the research: Conceptualization, Methdology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing-Original Manuscript, Visualization, and Project Administration. **Manuel Pérez Trujillo (corresponding author)** has contributed in the following stages of the research: Conceptualization, Methdology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing-Original Manuscript, Writing-Review Manuscript, Project Administration, and Supervision.

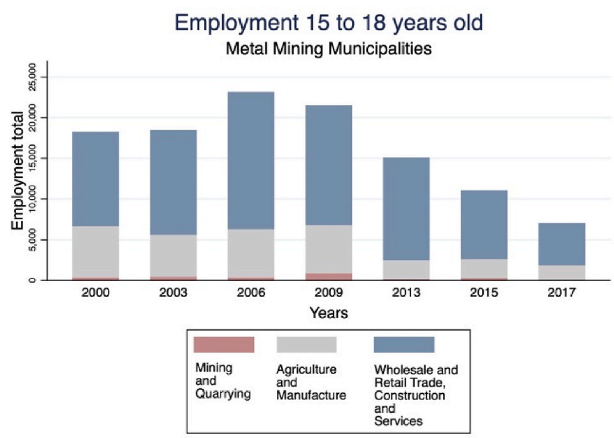
Appendix

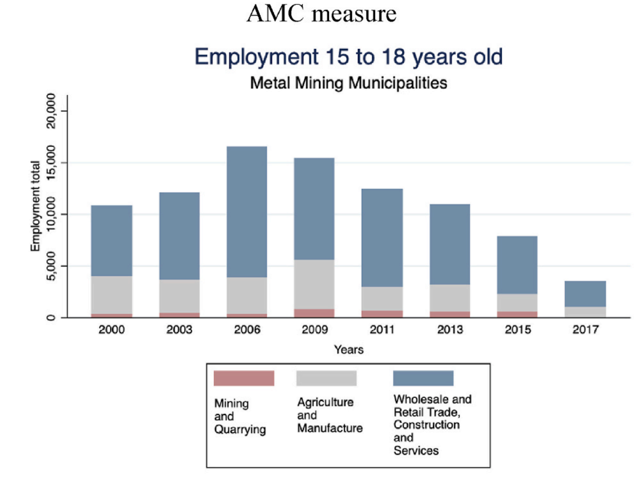
Table 7
Observations and main variables.

Label	Description	Mean	SD	Min	Max
$rate\_unemployment_{it}$	Unemployment rate.	8.17	4.19	0	33.55
$rate\_school\_enr_{it-l}$	(i) School enrollment rate for youth between 15 and 18 years old.	83.93	9.49	31.03	100
	(ii) School enrollment rate for youth between 18 and 24 years old.	37.08	13.69	0	97.2
$schooling\_returns_{it-l}$	Computed by applying a Mincerian wage equation.	7.55	6.17	−19.55	31.97
$rate\_part\_emp_{it-l}$	(i) Employment participation rate for youth between 15 and 18 years old.	10.69	7.67	0	62.07
	(ii) Employment participation rate for youth between 18 and 24 years old.	47.7	10.95	0	100
$Ln[P_{t-l,j}]$	The price index defined in logs.	4.97	0.45	4.2	7.07
z_{it}	Metal mining employment share in the year 2000.	1.56	4.37	0	28.22
$emp\_rate\_dif_{it-l}$	A proxy of the probability that a high-skilled worker has of being employed with respect to a non-skilled worker.	21.62	56.62	0	1048.92
$rate\_poverty_{\ it-l}$	Poverty rate calculated in percentage.	13.4	7.19	0	45.71

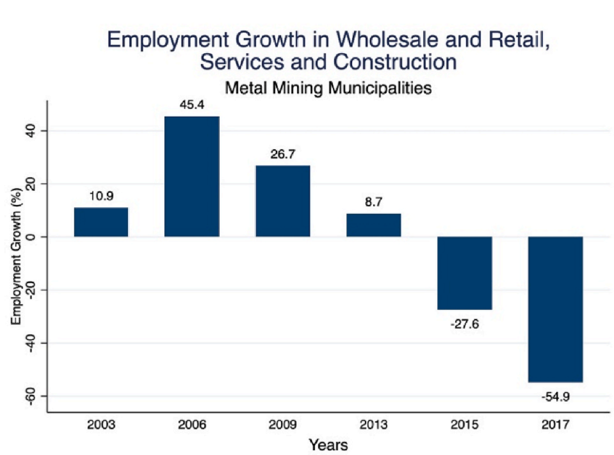
Source: Self-elaborated with CASEN 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017.
Note: The variable z_{it} is expressed as a dummy when using the AMC criterion to split the municipalities between mining and non-mining.

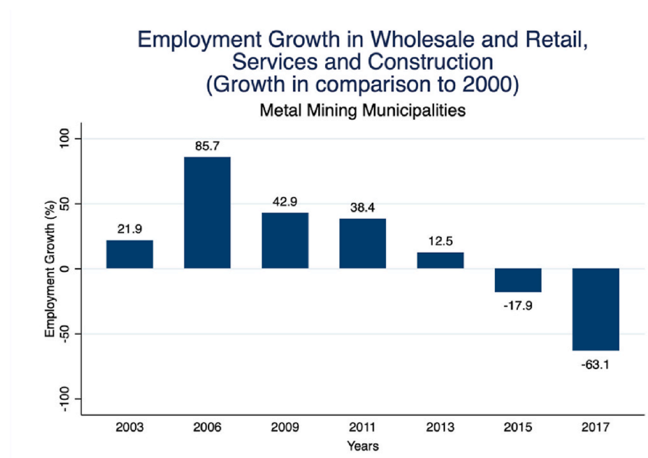
Weighted employment measure, Álvarez et al. (2021)　　　　AMC measure





(a)　　　　(a)





(b)　　　　(b)

Fig. A.1. Dynamic of employment by industry for Metal Mining Municipalities.
Source: Self-elaborated with CASEN 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: Employment growth is an expression comparing each year employment in the sector with the level of employment registered in 2000 for said sector.

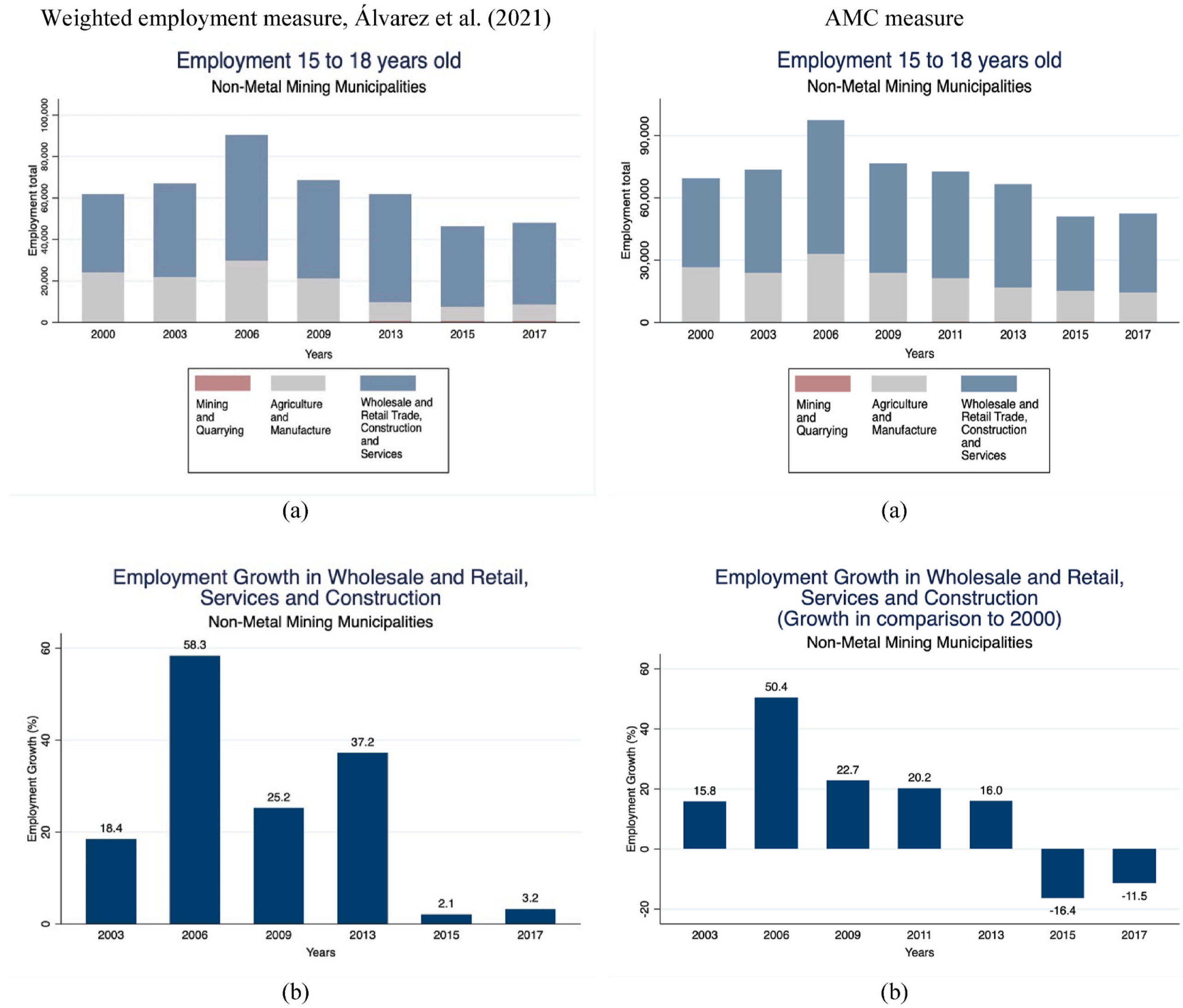


Fig. A.2. Dynamic of employment by industry for Non-Metal Mining Municipalities.
Source: Self-elaborated with CASEN 2000, 2003, 2006, 2009, 2011, 2013, 2015, and 2017. Note: Employment growth is an expression comparing each year employment in the sector with the level of employment registered in 2000 for said sector.

References

Abaidoo, R., Agyapong, E.K., 2022. Commodity prices, inflation and inflation uncertainty among emerging economies. Journal of Economic and Administrative Sciences. https://doi.org/10.1108/JEAS-10-2021-0203 (forthcoming).

Agüero, J., Balcázar Salazar, C., Maldonado, S., Ñopo, H., 2021. The value of redistribution: natural resources and the formation of human capital under weak institutions. J. Dev. Econ. 148 published online: 102581.

Altonji, J., Card, D., 1991. The effects of immigration on the labor market outcomes of less-skilled natives. In: Abowd, J., Freeman, R. (Eds.), Immigration, Trade and the Labor Market. University of Chicago Press, pp. 201–234.

Álvarez, R., García-Marín, Á., Ilabaca, S., 2021. Commodity price shocks and poverty reduction in Chile. Resour. Pol. 70 published online: 101177.

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

Arias, M., Atienza, M., Cademartori, J., 2014. Large mining enterprises and regional development in Chile: between the enclave and cluster. J. Econ. Geogr. 14 (1), 73–95. https://doi.org/10.1093/jeg/lbt007.

Atienza, M., 2021. No worker's land. The decline of labour embeddedness in resource peripheries. In: Irarrázaval, F., Arias-Loyola, M. (Eds.), Resource Peripheries in the Global Economy, Economic Geography. Springer, pp. 201–213.

Atienza, M., Modrego, F., 2019. The spatially asymmetric evolution of mining services suppliers during the expansion and contraction phases of the copper super-cycle in Chile. Resour. Pol. 61, 77–87.

Bebbington, A., Hinojosa, L., Bebbington, D.H., Burneo, M.L., Warnaars, X., 2008. Contention and ambiguity: mining and the possibilities of development. Dev. Change 39 (6), 887–914.

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

Berdegué, J.A., Hiller, T., Ramírez, J.M., Satizábal, S., Soloaga, I., Soto, J., Uribe, M., Vargas, O., 2019. Delineating functional territories from outer space. Latin American Economic Review 28 (1) article number 4.

Berman, N., Couttenier, M., Rohner, D., Thoenig, M., 2017. This mine is mine! How minerals fuel conflicts in Africa. Am. Econ. Rev. 107 (6), 1564–1610.

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

Bonilla, L., 2020. Mining and human capital accumulation: evidence from the Colombian gold rush. J. Dev. Econ., 102471 published online.

Borjas, G., 2003. The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. Q. J. Econ. 118 (4), 1335–1374.

Calero, C., Bedi, A.S., 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 labor market impacts of higher immigration. J. Labor Econ. 19 (1), 22–64.

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

Chávez, A., Rodríguez-Puello, G., 2022. Commodity price shocks and the gender wage gap: evidence from the metal mining prices super-cycle in Chile. Resour. Pol. 76 published online: 102497.

Contreras, D., Ruíz-Tagle, J., Sepúlveda, P., 2012. *Migración y mercado de laboral en Chile*. Serie de Documentos de Trabajo 376, Facultad de Economía y Negocios, Universidad de Chile, Santiago, Chile. Available in: https://repositorio.uchile.cl/bitstream/handle/2250/143732/Migracion-y-Mercado.pdf?sequence=1&isAllowed=y.
Corden, W.M., 1984. Booming sector and Dutch disease economics: survey and consolidation. Oxf. Econ. Pap. 36 (3), 359–380.
Daher, A., Moreno, D., Aninat, M., 2017. Efectos socioterritoriales en Chile del súper ciclo de los commodities y de su término. Metropole 19 (38), 127–155.
Drechsel, T., Tenreyro, S., 2018. Commodity booms and busts in emerging economies. J. Int. Econ. 112, 200–218. https://doi.org/10.1016/J.JINTECO.2017.12.009.
Farooki, M., Kaplinsky, R., 2013. The Impact of China on Global Commodity Prices: the Global Reshaping of the Resource Sector. Routledge, London, UK.
Ferreira, F., Schady, N., 2009. Aggregate economic shocks, child schooling, and child health. World Bank Res. Obs. 24 (2), 147–181.
Figueroa, B.E., Calfucura, T.E., 2003. Growth and green income: evidence from mining in Chile. Resour. Pol. 29 (3–4), 165–173.
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. Econom. 107 (6), 65–94.
Greene, W., 2012. Econometric Analysis, seventh ed. Pearson, New York, US.
Guimbeau, A., Ji, J., Menon, N., van der Meulen Rodgers, Y., 2020. Mining and Gender Gaps in India. Institute of Labor Economics (IZA) #1388, Bonn, Germany.
Hernández, L., Atienza, M., Modrego, F., 2022. Is Industrial Related Variety an Enabling Condition for Regional Entrepreneurship? A Comparison between Mining and Non-mining Regions in Chile. The Extractive Industries and Society published online: 101096.
International Labor Office ILO, 2018. El mercado laboral en Chile: Una mirada de mediano plazo. ILO Informes técnicos/4 año 2017, Santiago, Chile.
Kabwe, E., Yiming, W., 2015. Analysis of copper's market and price-focus on the last decade's change and its future trend. Int. J. Scientif. Technol. Res. 4 (10), 54–61.
Karlsson, C., Johansson, B., Stough, R., 2010. Entrepreneurship and Regional Development. Edward Elgar Publishing, Cheltenham, UK.
Krugman, P., 1987. The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: notes on trade in the presence of dynamic scale economies. J. Dev. Econ. 27 (1–2), 41–55.
McKenzie, D.J., 2003. How do households cope with aggregate shocks? Evidence from the Mexican peso crisis. World Dev. 31 (7), 1179–1199.
Measham, T.G., Fleming, D.A., 2014. Impacts of unconventional gas development on rural community decline. J. Rural Stud. 36, 376–385.
Modrego, F., Berdegué, J.A., 2015. A large-scale mapping of territorial development dynamics in Latin America. World Dev. 73, 11–31.
Morissette, R., Chan, P., Lu, Y., 2015. Wages, youth employment and school enrollment: recent evidence from increases in world oil prices. J. Hum. Resour. 50 (1), 222–253.
OECD, 2018. OECD Economic Surveys: Chile 2018. Paris, France.
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.
Pérez-Trujillo, M., Rodríguez-Puello, G., 2021. Economic shocks and their effect on the schooling and labor participation of youth: evidence from the metal mining price boom in Chilean counties. Ann. Reg. Sci. 68, 65–93.
Poelhekke, S., van der Ploeg, F., 2007. Volatility, financial development and the natural resource curse. In: Handbook of Development Economics.
Radetzki, M., Eggert, R.G., Lagos, G., Lima, M., Tilton, J.E., 2008. The boom in mineral markets: how long might it last? Resour. Pol. 33 (3), 125–128.
Rehner, J., Vergara, F., 2014. Efectos recientes de la actividad exportadora sobre la reestructuración económica urbana en Chile. Rev. Geogr. Norte Gd. 59, 83–103.
Sachs, J.D., Warner, A.M., 1995. Natural Resource Abundance and Economic Growth. National Bureau of Economic Research #w5398, New York, US.
Schady, N.R., 2004. Do macroeconomic crises always slow human capital accumulation? World Bank Econ. Rev. 18 (2), 131–154.
Singleton, K.J., 2014. Investor flows and the 2008 boom/bust in oil prices. Manag. Sci. 60 (2), 300–318.
The Observatory of Economic Complexity, 2022. Copper Ore. Retrieved May 18, 2022, from. https://oec.world/en/profile/hs/copper-ore.
Tilton, J.E., 2006. Understanding Cyclical and Secular Trends in Metal Prices. International Mine Management Handbook. Australasian Institute of Mining and Metallurgy.
Zimmermann, L., 2020. Remember when it Rained – Schooling Responses to Shocks in India, vol. 126. World Development published online: 104705.