“Commodity Prices Shocks in Chile
Local Effects on Poverty, and Transmission Mechanisms”

TESIS PARA OPTAR AL GRADO DE

Magister en Análisis Económico

Alumno: Sebastian Alberto Ilabaca Turri

Profesor Guía: Roberto Álvarez

Santiago, Abril 2016

Commodity Prices Shocks in Chile
Local Effects on Poverty, and Transmission Mechanisms

Sebastián Alberto Ilabaca Turri
Teachers Guides: Roberto Álvarez & Álvaro García

Abril 2016

Abstract

The commodity prices shocks at the beginning of 2000's had important effects in Chile, where one of the most relevant shock was on metal-mining products. This investigation examines the local economic impact on poverty of the metal-mining commodity prices boom for the country, and the transmission mechanisms of those effects. We use household data between 1998 - 2013 to create a panel data at municipality level, and exploit the differences in municipalities exposure to change in prices. The results shows a reduction in poverty rates associated with the positive terms of trade shock, where the magnitude depends on the exposure level. Counties belonging to the 95th percentile of the exposure level had on average a poverty reduction of 1.95 percentage points (pp) due to the shock. We also examine the labor markets transmission mechanisms, finding that the shock generates an increase in unskilled workers employment and wages. On average, for the latter group of municipalities the commodity shock produce an increase of 1.07% in unskilled metal-mining employment, and 6.69% in unskilled workers wages.

Contents

1 Introduction

Latin America is a strong exporter of natural resources to developed countries, and Chile is not the exception. Historically and actually Chile is on the top of mining product exporters. Today, for the country the metal-mining products owns the biggest share of total exports, where cooper is for far the most important metal. Over the last decade several developing countries have experienced positive and large terms of trade shocks. The developed countries explain a small share of this shocks, but it was China with a strong and sustained growth (9.6% on average between 1998 and 2013 and 10.2% between 2003 and 2013[1]) demanding commodities who explain this boom in prices [Yu, 2011] & [Farooki and Kaplinsky, 2013].

The boom could have negative effects for countries if we are in presence of Dutch Disease, where this theory predicts a negative impact, in long terms, for the GDP growth by appreciating the exchange rate and contracting the manufacture and other industries that provides structural and sustainable economic growth (by generating human capital, productivity gains, and others positive externalities) [Corden, 1984] & [Krugman, 1987]. Moreover, this should also affect economic growth adversely according to the literate on "Natural Resource Curse" [Sachs and Warner, 2001] & [Sachs and Warner, 1999].

Nevertheless, this phenomenon may have different effects depending on the country and it's institutions. Indeed, the empirical evidence of those theories are controversial, but a common consensus between economists is that the quality of institutions are determinant to have negative or positive effects due to natural resource booms. Negative effects should be more prevalent in economies with week institutions [Ploeg, 2011]. For instance [Mehlum et al., 2006] shows that the negative impact of natural resources abundance is only observed in economies with inferiors institutions, but not in countries with high institutional quality. [Robinson et al., 2006] explains this differences about the impact of resource booms, showing that economies with institutions that promote accountability and state competence are able to ameliorate the perverse political

[1] Using data from the World Bank: Annual GDP growth at constant prices, expressed in US$ dollars.

originated during the resources booms.

In this context, the fact that developing countries had a good performance, in terms of economic growth, between the past decade and the recent financial crisis - in particular to Latin American countries - challenges in part this wisdom that natural resource abundance (or booms) would be detrimental for economic performance. In addition, [Gregorio, 2014] shows that Latin American resource abundance countries, and specially Chile, not only experienced strong economic growth during that period, but also were less affected by the last global financial crisis, compared to previous ones.

However, economic growth is not the only important variable in this phenomenons. We know very little about the impact of commodity shocks prices on other measures or dimensions of social welfare, for instance poverty or income distribution, how this shocks are transmitted to local communities, and the heterogenity of this shocks between more exposure communities and less exposure ones.

Our investigation contribute to this literature of local market effects of resource booms by analyzing the impact of the metal-mining prices shock on poverty rates across municipalities in Chile, during 1998-2013. We exploit the exogenous price changes, due to China's increasing growth in the period, in five metal minerals products - the most important for Chilean economy - and the different exposure of each municipality to this positive resource boom. This within-country analysis is particularly interesting in a economy like Chile for two reasons: First, because the price changes we examine is over to commodities, so this is a largely exogenous shock; and second, because Chile is highly dependent on mining exports, specially in cooper products, and third because the metal-mining activity is distributed heterogeneously across municipalities. These characteristics allows as to differentiate the exposure of each municipality to the exogenous price shock.

But also, there could be others explanations for poverty reductions instead of the commodity shock. In this investigation we analyze four possible alternative explanations to explain the higher poverty reductions in municipalities exposed to the shock, as part of our identification strategy. These alternative explanations are: Trends, Plants Location, Poverty Convergence, and Political Economy[2].

In addition, we not only examine the impact on poverty rates, but also we focus our analysis on the transmission mechanisms of those effects. To do that, we analyze the two major mechanisms of labor market that we believe are the most important channels to reduce poverty: employment and wages. About the employment rates, we examine the impact over different workers skills. Table A3 in Appendix 11 shows that metal-mining industry is highly intensive in unskilled workers so the transmission mechanisms should be over the employment and wages of unskilled workers, due to the increase in metal-mining industry demand of those workers.

From other side, the empirical model is a Difference in Difference estimation with fixed effects, which allows as to control for unobservable variables that doesn't vary over time -time fixed effects-, an also for local fixed effect - for each municipality - to control for potential structural characteristics of municipalities. Also, we exploit the difference in the exposure to the shock to capture the heterogeneity of the shock-effect.

The results of the estimations shows that the effect of the commodity shock is significant on poverty rates reductions, and the transmission mechanisms that drives those reductions are employment and wages of unskilled workers. The mainly reason is that metal-mining industry is very intensive in unskilled workers, so the shock increase the demand which also increase the wages. Nevertheless, the magnitude of those effects depends on the exposure level of municipalities: higher exposure means higher effects over poverty, employment and wages. At the end of Section 7 we presents the average effects over poverty, total employment, unskilled metal-mining employment, total wages, and unskilled wages for different exposure levels. For the simple average of exposure level across municipalities the shock reduce poverty in 0.68 percentage points, increase total and unskilled metal-mining employment in 0.34 and 0.45 pp respectively, and increase total and unskilled wages in 2.58% and 2.35% respectively.

A very important issue to take account when we look at poverty rates is the heterogeneity

[2] We explain in detail each one of them in Section 6.2

in the cost of living across the country. Chile is the longest country in the world so it's not rare to find that prices differs over geographic zones, and if prices increases more in exposed municipalities that could mean that their poverty rates were underestimated and therefore our estimations could be biased. First, we construct the Hedonic prices for rental cost in apartments and houses, considering that rental cost as an approximation of price evolution of non-tradable goods and services. Second, since there is no official Consumers Price Index at a municipal or regional levels, we construct a Municipal Consumers Price Index (MCPI) using CASEN's data for the period of 2000 to 2013. The source of heterogeneity comes from the rental cost of apartments and houses. With this index we find that although the index increase more in municipalities exposed to the shock, it doesn't look like a problem to our conclusions since wages also grew faster for those municipalities.

Finally, we complement our analysis by introducing several robustness checks: The first is a falsification analysis; the second is sample restrictions in three ways: (*i*) excluding the Metropolitan Region, (*ii*) restricting the sample to period from 1998 to 2009, and (*iii*) restricting the sample to only the repeated municipalities surveyed in the whole period; in third place we analyze if shock in other commodities relevant to the economy are important to movements in poverty and the transmission mechanisms; the fourth is changing the measure of poverty rate from an absolute measurement to a relative one; fifth, we analyze the possibility of an overvaluation of the effects due to migration across counties; then, in the sixth check we induce changes in the measure of the variable for the exposure level; and finally our seventh and eighth robustness checks are analyze if Dutch Disease and female employment are important as alternative of transmission mechanisms.

This work is structured as follows. The next section is a literature review of local effects due to shocks. In the third section we describe the data we use, and the main stylized facts on the relationship between prices, the metal-mining industry, and poverty rates over the past decades. In the fourth section we detailed the theoretical model which guides our intuitions. The empirical model used to estimate the effects are presented in the fifth section, and then in the sixth section we present the main results of those estimations and the analysis for the heterogeneity in the cost of living across municipalities. The seventh section display the estimations for the transmission mechanisms driving the effects, an the following section shows the robustness checks of the estimations. Finally, the core findings and conclusions are discussed in the last section.

2 Literature Review

The within-country, or local effect, literature is relatively abundant and it belongs to a more general literature known as "Resource Curse". This last literature starts with [Sachs and Warner, 1995] who found a negative relationship between natural resource abundance and economic growth, but this evidence will be refuted by [i Martin and Subramanian, 2003] and other authors who included the variable of institutional quality. They determine that controlling by institutional quality the effect of resource abundance is no significant, or it could be heterogeneous: negative to those with bad institutional quality, and positive o non significant to economies with high quality, according to [Robinson et al., 2006]. Finally, in part supporting the original idea of the resource curse, there is the work of [Sokoloff and Engerman, 2000] who argue that the abundance of natural resources affected negatively, at the beginning of the American colonies, to their institutional development. Countries with resources abundance develop extractive institutions, which derived in high inequity on income distribution and a political power captured by the dominant economic class.

But our work is framed in the literature that analyze the local effects of the resource abundance (or resource booms) and trade-related shocks, rather than effects between countries. It's a contribution to this emerging literature of within-country analysis, with heterogeneous effects over the economy. Nevertheless, there is quite empirical evidence that tries to capture the effects of this effects over local communities. [Aragon et al., 2015] writes about this literature and develop a simple analytic framework of how resource booms can affect local communities, highlighting (1) Dutch Disease, generating lower technological progress and long term growth;

(2) volatility in Terms of Trade, that can promote wrong public policies; and (3) political economy argues, like corruption, rent-seeking, social conflict, and others. The last two mechanisms rest in the assumption of have bad quality of institutions.

About Dutch Disease, [Allcott and Keniston, 2014] study if there is Dutch Disease in U.S. counties that are abundant in oil and gas, after a shock in that industry. The shock is measured as positive employment changes in those sectors, and they estimates the effects over the productive structure, wages, employment and economic growth. In particular, they found that the effects on manufacture industry are ambiguous - a big share of manufacture industry is benefited because creates inputs to oil and gas industries - and that the shock had positive effects over wages and employment, but they're reversed in long term.

From the side of economic policy mechanisms, [Caselli and Michaels, 2009] explores the impact of an increase in municipalities resources, due to oil production windfalls, on welfare. The results shows no significant effects over several variables of social welfare in households, highlighting that apparently the corruption in municipal governors is behind this results. Similar approaches have been also used to evaluate the impact of Indian trade reforms on schooling and child labor [Edmonds et al., 2010], and over poverty and consumption [Topalova, 2010][3]

In addition, [McCaig, 2011] investigate if poverty can be reduced by a bigger access to rich countries. The author examines how the U.S. - Vietnam Bilateral Trade Agreement (BTA) affects provincial poverty in Vietnam. Exploiting different exposure to changes in U.S. tariffs, due to differences in labor force structure, he finds that lower tariffs were associated with a reduction in poverty. He also explore the transmission mechanisms finding that a faster wage growth in unskilled workers was the mayor channel of those effects. This empirical investigation is very similar to our work, and the methodology he used - a Differences in Differences estimation - is an important input to our econometric model.

[3] See also [McCaig and Pavcnik, 2014], [Howie and Atakhanova, 2014], and [Marchand, 2014].

3 Background and Data

We begin this section describing the data we use in this investigation, and how we work it. In second place we describe the main variables used, and how we are defined. Finally, we provide background on the metal-mining industry, and the commodity boom of mid 2000's and it's effects on Chilean local communities. Finally, we present preliminary evidence of the commodity price shock on local poverty and income.

3.1 Data

The main dataset we use in this investigation is the Chilean National Socioeconomic Characterization (CASEN) survey, which is a household survey applied by the Chilean Social Development Ministry (MIDEPLAN or MDS) every two or three years. This survey is the main source of Chile's socioeconomic statistics - such as official poverty rate -, and it´s information is periodically used to assess the impact of social policies and programs. Indeed, the fundamental purpose of CASEN is to measure correctly the poverty rate. On average, CASEN includes survey information of about 65.000 households in 290 municipalities -around 1.5% of total population (see Table A1 in Appendix).

CASEN is available from 1985, nevertheless we start our analysis in 1998, because the municipal coverage of earlier CASEN versions is significantly lower[4]. For that in this work we use the seven CASEN waves ranging from 1998 to 2013. The fact that the commodity boom of 2004 is just halfway in between the beginning and end of our sample is important to our study, because it allow as to control for pre-shock trends in the poverty rate, and to study short and medium-term effects of the commodity boom on poverty, wages and employment[5].

[4]For instance, CASEN surveyed only household from 126 municipalities in 1996 - about 40 percent of the average number of municipalities covered in 1998-2013 and two-thirds of the municipalities surveyed in 1998.

[5]Specifically, we use three waves before the beginning of the commodity boom in 2004 - the 1998, 2000 and 2003 CASEN's -, and four waves after the shock - 2006, 2009, 2011 and 2013 CASEN's -.

We aggregate the original data at a municipal level, the smallest administrative unit in Chile. In principle, the analysis could also be performed at different aggregation level (region, provinces or individual level) but there is some problems associated. We do not use a more aggregated level (region or province) because municipalities look more similar to the concept of local labor markets. The region consists of several provinces and municipalities, in some case covering large distance between municipalities, which indicates that it's a very broad aggregation for looking at impacts on local labor markets. This is also valid for most of provinces, but not for all of them especially those where the capital of the country - Santiago - is located. In addition, it usually occurs the case that not all municipalities within provinces are surveyed every day - from one CASEN to another we could have more or less municipalities surveyed for one province -. This implies that using the data at the level of province would likely result in non-representative results.

For the case of individual aggregation level we could have several problems for the identification of general equilibrium effects -such as spillovers to other sectors not related directly to the commodity sector -. Therefore, in the absence of more detailed information of commuting, we employ municipalities as our unit of study. Once we define our unit of study we have a consolidated database of 1452 observations (335 municipalities). For our main regressions we have 1356 observations in 196 municipalities, but when we restrict our sample to municipalities that repeat over the seven CASEN's of 1998-2013 we have 1264 observation in 182 counties.

On the other side, we need information of price and production of the main metals produced in Chile to create our variables of interest and quantify the exogenous shock for each year. The data on metal's prices and production are from *Chilean Cooper Commission* (COCHILCO) - at a national level - and the IMF's *Macroeconomic Statistic Database* when there is missing data from COCHILCO. Finally, for our robustness checks we include data of the *Electoral Service* (SERVEL) to categorize the political inclination of municipality's Mayors according to their political party, and geographic location data of the main cooper producer companies, also provided by COCHILCO.

3.2 Main Variables

We have two main variables in this study: poverty rate, and the variable that captures the shock - later we'll call it *Metal's Price Index* -. For each municipality c in period t we define the poverty rate σ_{ct} as:

$$\sigma_{ct} = \frac{\sum_i^I w_{ict} I(y_{ict} < \bar{y}_t)}{\sum_i^I w_{ict}}$$

Where $I(y_{ict} < \bar{y}_t)$ is an indicator function that takes the value one if individual i of municipality c in time t has an income y_{ict} below the poverty line $\bar{y}_t$. w_{ict} are weights given by the expansion factor -at a municipal level- provided by CASEN. To define poverty we use the Chilean official poverty line -comparable to all periods- which is defined in terms of a minimum bundle of products necessary to satisfy dietary requirements[6]. Note that by following the official definition of poverty we are assuming that the cost of life is equal across municipalities, which is a strong assumption. If there is price heterogeneity across municipalities our results may be biased, because the real poverty rate downward could be lower in municipalities intensives in metal-mining employment if in that municipalities the cost of living is higher. This is one of the most important points of this investigation: to take care about cost of living heterogeneity, and we address this point in Section 6.3.

With CASEN's data we build other series of variables to be use either as outcome variables or as controls. These of variables are: (*i*) the average wage of unskilled workers (high-school or lower), and skilled workers (some post-secondary education), (*ii*) the average years of schooling, (*iii*) the share of people living in urbane zones, (*iv*) the county size, (*v*) the average size of households, and (*vi*) the share of metal-mining employment. In order to have a correctly comparison in average wages for counties, we only consider individuals with age between 15 and 65, and working more that 80 hours at week [7]. For more detail about the construction of this

[6] The composition of the bundle is determined by the Economic Commission for Latin America and the Caribbean (ECLAC), based on the minimum caloric requirements advised by the World Health Organization and the Food and Agriculture Organization.

[7] Also, we exclude those who declare been working in national military groups, or as unpaid family.

variables see Table A2 in Appendix.

On the other side, our second main variable captures the metal's price variation of mid-2000's commodity boom. This variable is an index called *Metal's Price Index*, representing the price variation of all metal's that cover more that 1% of the overall production value in 2003. Five metals fall under this criterion: Cooper, Silver, Gold, Molybdenum, and Iron Ore[8]. We define for each period t the average percentage change in metal's price $\tilde{P}_t$ as:

$$\tilde{P}_t = \frac{\Delta \bar{P}_t}{P_t} = \sum_{i=1}^{5} \theta_i^{98} \frac{\Delta P_{i,t}}{P_{i,t}}$$

The subscript i represents each of the 5 metals defined previously, θ_i^{98} is the production value share of each metal i (scaled by the production value of all five metals, so that they add up to one), and $P_{i,t}$ is the nominal price of each metal. Finally, we compute the *Metal´s Price Index* τ_t as:

$$\tau_t = (1 + \tilde{P}_t) \cdot \tau_{t-1}, \quad with\, \tau_{2003} = 100$$

3.3 The Metal's Commodity Boom

The mid-2000's "super-cycle" has been one of the largest commodity booms of the last 100 years. Between 2003 and 2008 oil and metal's prices tripled, and food and precious metals doubled [Baffes and Haniotis, 2010]. Almost a decade after the beginning of the boom, there is consensus among scholars and market analysts that the boom was mostly caused by demand pressures from emerging countries - in particular China - rather than from general increase in marginal costs (as it was the case of the 1975-1980 boom)[9]. This is essential to our study,

[8] These metal's represent aver 99.5% of all the production value in 1998-2013. Out of this metals, cooper is the most important by far: it account for over 85% of the total production value each year. Figure 7 shows the international price and Chilean production (normalized in 2003) of these five metal's for the sample period.

[9] [Erten and Ocampo, 2013] make a more general point and show evidence that suggest that all "supercycles" from 1865 to 2010 for non-oil commodities were essentially demand-driven.

because it implies that most of the *initial shock* to international prices are largely exogenous for a commodity producer country such as Chile.

The commodity boom had a positive effect in activity in most of commodity producing countries. As we said, the Chilean case has some characteristics that makes it particularly interesting, where the most important is that is a large-scale producer of metals and its economic activity strongly com-move with the price of Cooper, it main metal. Chile is not only the world's largest producer of cooper, but it's also within the top-three largest producers of Molybdenum (U.S. Geological Service). The price of this two metals experienced substantial rises during the commodity boom: Cooper price went from about USD 0.80 per pound in 2003 to over USD 4.00 per pound in the second quarter of 2008, and molybdenum jumped from USD 3.3 to about USD 32.5 per pound over the same period, a ten-fold increase. Over the same period, tax revenues - largely dependent on Chile's main state owned mine revenues, CODELCO's - jumped significantly, and employment and economic activity flourish in mining regions (see [COCHILCO, 2014]).

The Figure 1 shows the evolution of the Metal's Price Index and poverty rate - differentiating the poverty rate at metal-mining intensive and non metal-mining intensive municipalities - over the sample period. But focusing only in the Metal's Price Index, we can see that for the period of 1998 to 2003 the index remained relatively stable. Then, from 2004 onwards the price index shows an increasing trajectory. In 2004 the price index jumped about 40% over the previous year, while in 2006 the price index was almost three-times higher than in 2003. After a relatively short decrease from 2006 to 2009 -where the metal's price stabilized and had a brief collapse in 2009 following the onset of the sub-prime financial crisis- the metal's price index recovered his previous values quickly in 2010, and from 2010 to 2011 the index reached its peak rising almost 73% in that year.

3.4 Preliminary Evidence on Poverty, Wages and Employment

As we said before, our econometric model is a Differences in Differences estimation. For this to be meaningful, the poverty rates trajectory should diverge between metal-mining municipalities and non metal-mining ones. Indeed, we should expect that, on average, poverty rate in municipalities where metal-mining is a relatively important activity decreased more than other municipalities - non intensive in metal-mining -. Furthermore, if the previous trends -before the boom- of those municipalities were moving in a similar way, that would be supporting our hypothesis.

But previous to the comparison, one of the key aspects in this analysis is the definition of metal-mining and non metal-mining municipalities. In principle, we could define metal-mining municipalities in terms of their economic activity (i.e., production). However, this could lead to misleading results if workers moves across municipalities to work[10] - live in different municipalities where they work -. Fortunately, CASEN allow as to deal with this issue: it provides information for the economic activity of each member of the household, independently on the geographic location of the job. This implies that the employment share in the metal-mining sector of a given municipality may be relatively high, even if there is no mines or mineral deposits located nearby. Thus, we opt for using metal-mining employment to determine the degree of exposure to the boom of municipalities. In particular, we define metal-mining (non metal-mining) municipalities when the metal-mining employment share is above (below) to 1% in 1998 - which roughly correspond to the upper quartile of 1998 employment share distribution. This arbitrary threshold was a consensus among the investigators, but the selected municipalities are the same than taken the counties with some metal-mining workers -have at least one worker in metal-mining industry- and putting the threshold in the median of the distribution[11]. With this criterion there are 50 counties intensives in metal-mining industry, where analyzing the

[10]This is a certain possibility in mining, where workers tend to work in non-standard shifts, such as 7x7 (7 days working in the mine and 7 seven days resting) or 4x3.

[11]This means that metal-mining counties are those with a share of metal-mining workers above the median of the distribution only for counties with metal-mining employment share higher than 0.

distribution we find that forty are between the 75th and 95th percentiles, eight are between the 95th and 99th percentiles, and only 2 are in the last percentile.

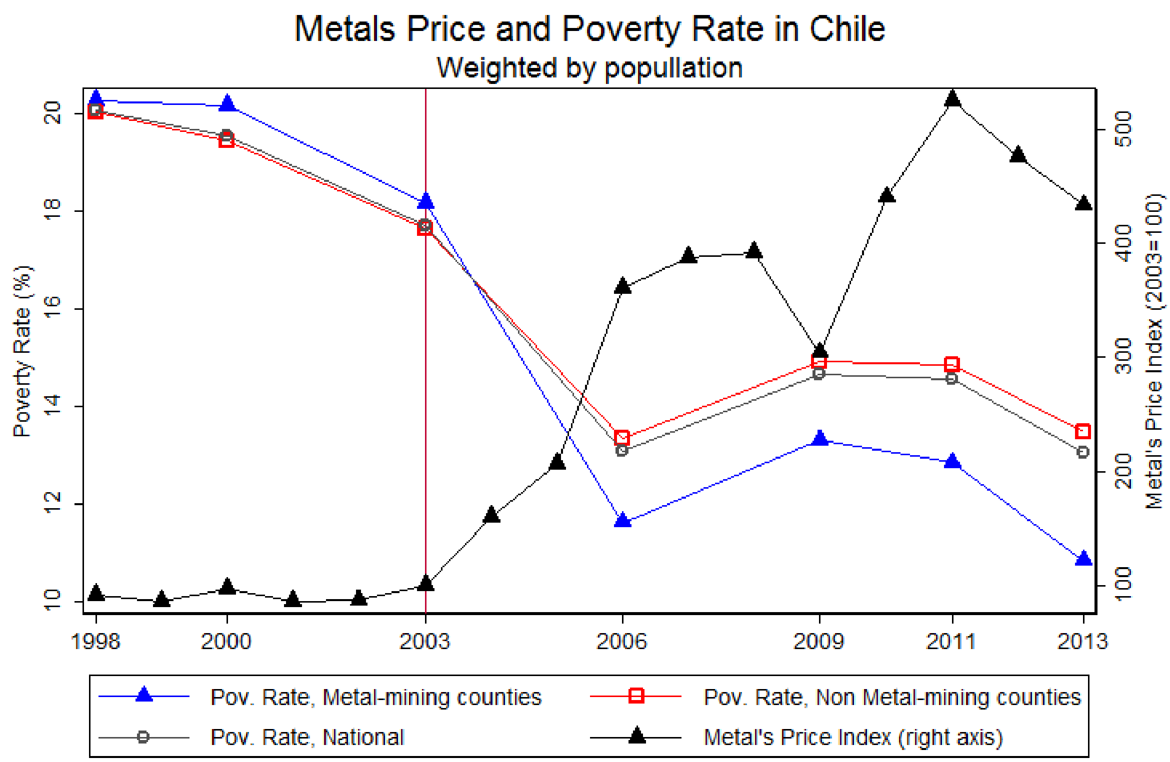

Figure 1: Poverty and Commodity Shock

Figure 1 shows three poverty rates: at a national level, and for metal-mining and non metal-mining municipalities. As it can bee seen, our hypothesis is fulfilled. First, between 1998 and 2003 - before the boom - the poverty rates shows a moderate declining from 1998 to 2003, with common trends to both type of municipalities. In addition, poverty rates were relatively close between metal-mining and non metal-mining municipalities. In this period national poverty rate shows a moderate decline, from 20.1% to 17.7%. Then, in 2006 the poverty rate experience a sharp decline from 17.7% to 13.07%. But the important thing is that after the boom we see that the poverty rate decline is significantly larger in metal-mining municipalities. While in non metal-mining municipalities poverty rate fell from 17.6% to 13.3%, the decline in metal-mining municipalities was much larger -about 2.3 percent points larger-, from 18.2% to 11.6%. Apparently, the commodity boom creates a big poverty rates gap between metal-mining and no metal-mining municipalities. In 2009, after the financial crisis in 2008, poverty increased, but interestingly the poverty rate gap between those types of municipalities remains constant in about 1.7 percentage points. Then between 2009 and 2013 the gap was even widened to approximately 2.6 percentage points.

That's about poverty and the commodity prices boom, but we also have preliminary evidence of wages and employment: our transmission mechanisms. Looking at Table A3 in Appendix 11 - created with CASEN's data - it can be notice that metal-mining industry is highly intensive in unskilled workers, mostly because of the productive structure where firms needs many low quality workers to extract the minerals. According tho that, we should expect that the commodity boom increase firm's demand of unskilled workers, pressing upwards the wages of those workers.

Figure 2 shows the metal-mining employment evolution over the sample years. The graph from the left interact the skilled, unskilled and total share of metal-mining employment over the total employment in the country. The total metal-mining and skilled workers had a small growth - from 1.17% to 1.25%, and 0.32% to 0.46% respectively between 1998 and 2003 - previously the boom, while unskilled shows a tiny decreased - from 0.85% to 0.78% - in the same period. After the commodity shock the total metal-mining employment share strongly increases 1.25% to a maximum of 2.4% in 2011 - almost double -, but the trends of skilled and unskilled workers share are reversed: unskilled workers rises sharply - with a peak of 1.82% in 2011, more than double than 2003 -, while skilled workers decreased in the short term and then shows a small rise to 0.64% in 2013. This mean that the increased in total metal-mining employment was mostly guided by hiring unskilled workers. From other side, the graph from the right shows that the composition of skilled-unskilled workers in metal-mining industry changes strongly in favor of unskilled workers, corroborating the left-graph.

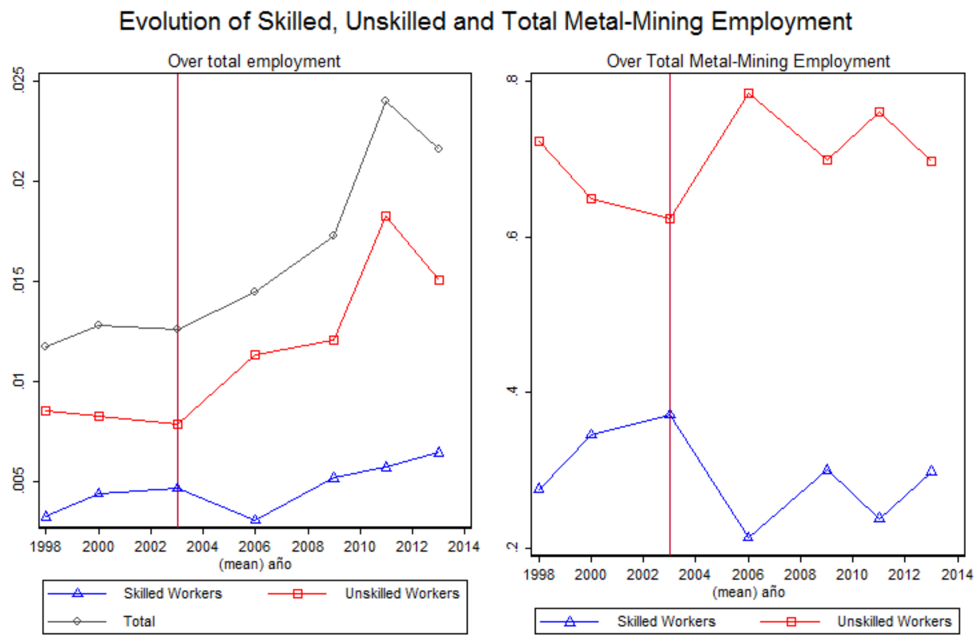

Figure 2: Evolution of Metal-mining employment

Finally, Figure 3 compares wages -in natural logarithm- of metal-mining skilled and unskilled workers, with non metal-mining ones. For the skilled workers there is not a clearly predominance of one type of workers, but rather it looks like wages stays relatively stable - indeed, for skilled metal-mining workers the wage in 2013 is almost the same than in 2000 -. Nevertheless, the graph from the right is quite different. Wages of unskilled metal-mining workers moves with the same trends than the rest of the unskilled workers after the boom - on the contrary, before the commodity shock wages had divergent trends -, so is difficult to determine if the shock had a significant effect on unskilled metal-mining workers and not in all unskilled workers wages. The econometric analysis would determine this last issue, but apparently the data is clear showing that our hypothesis goes in the right direction.

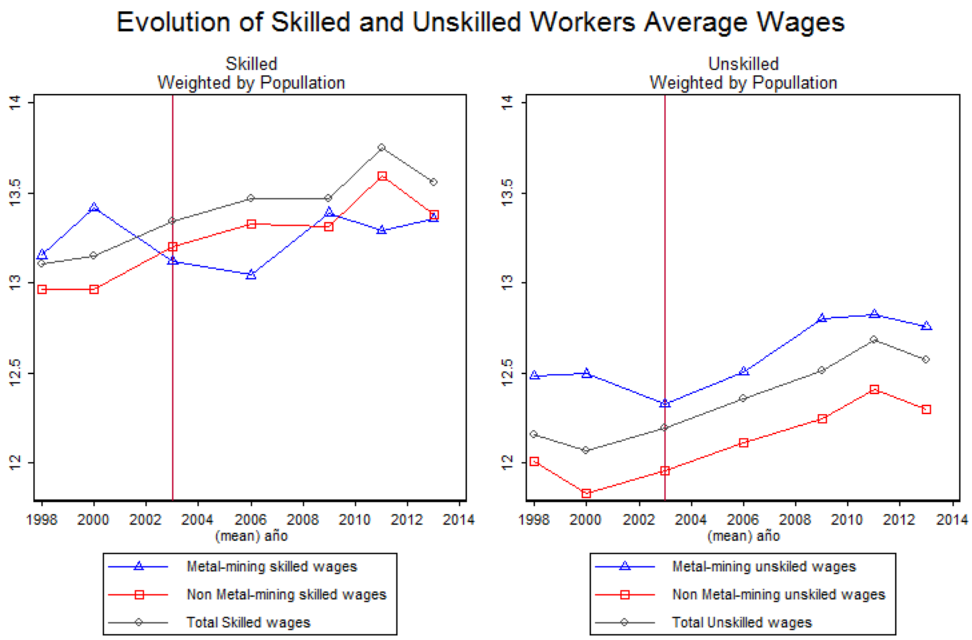

Figure 3: Skilled and unskilled workers wages

4 Theoretical Model

Up to now, we have an hypothesis that makes sense looking at data. Indeed, in the previous section we show that, just looking variables evolution, our hypothesis is apparently corresponded with the data analysis. Poverty decreased more in metal-mining municipalities, employment rises strongly for unskilled workers in the metal-mining industry, and wages of those workers shows a big increase, while skilled workers wages remains relatively constant. But our hypothesis in not just to the data, but also to the theory.

Indeed, a simple model of international trade as the "Specific Factors Model" -developed by Pauls Samuelson & Ronald Jones- is behind this hypothesis and help as to explain the rationality of the effect over poverty rates and the transmission mechanisms guiding the effects. In this international trade theory we have two industries: Mining (M_i) and Manufacturing (M_a), where mining industry uses Land (T) and Labor (L) as productive factors, and manufacturing uses capital (K) and also labor. Labor is the only factor that moves across industries, while the others are fixed [Krugman et al., 2006].

Figure 4 shows the equilibrium of this model, where the wages of both industries are equal, and it's level are determined by the value of labor marginal productivity, that also have to be equal between industries. The equilibrium point is obtained by the following expression:

$$PmgL_{M_i} \cdot P_{M_i} = PmgL_{M_a} \cdot P_{M_a} = w^*$$

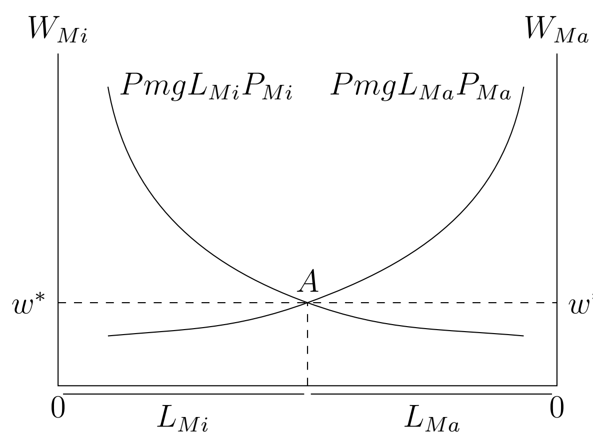

Figure 4: Equilibrium in Specific Factors Model

Industrial wages must be the same due to mobility of the labor factor, nevertheless in short term exists transaction costs that implies a relatively low mobility of workers. Indeed, the process to change from one industry to another is slow and costly. In that way, external shocks that increase the value of labor productivity could end in different wages between industries, due to transaction costs. Applying this to Chilean case, the commodity boom is an increase of mining products from P to $P^{'}$. Figure 5 shows that external shock and how it's affect the equilibrium.

As can be notice, we implicitly named the two transmission mechanisms of our analysis: employment and wages. Then, as we said in our hypothesis, we should expect a negative effect

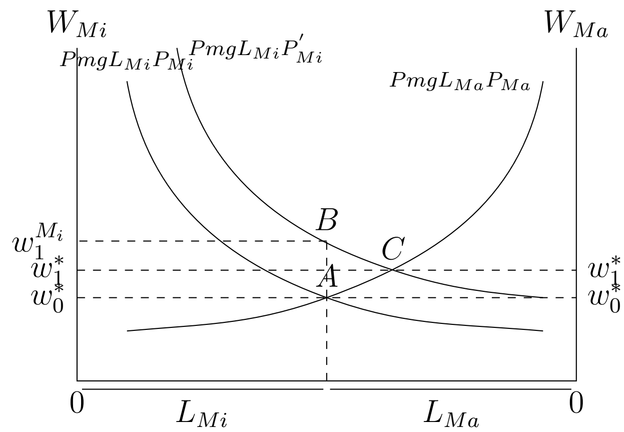

Figure 5: Effect of a price increases in Mining Sector.

over poverty rate because of mining industry structure: highly intensive in unskilled workers - which they are clearly more likely to be poor -. This simple model and the structure of metal-mining industry guide our hypothesis. A descriptive statistic analysis in the previous section apparently corroborates our hypothesis, but now we need an econometric model to test it empirically.

5 Econometric Model

To analyze the impact of price changes in metal-commodity minerals on poverty rates, we follow a difference-in-difference approach and exploit the difference in exposure to the changes. Given that the price shock is exogenous, but it could be negatively correlated with unobservables trends, we estimates versions of the following final equation:

$$y_{c,t} = \alpha_c + \alpha_t + \beta Log(P_t) \cdot \theta_{c,98} + \lambda' X_{c,t} + \varepsilon_{c,t} \tag{1}$$

Where y_{ct} is the poverty rate (or the outcome variable) at county c in year t, P_t the metal mining prices index described in the previous section, θ_c is our measure of exposure of county

c in year 1998 to changes in P_t, and X_{ct} is a set of variables for the characteristics of each municipality and year. Our baseline results are derived using the share of metal-mining sector on each municipality overall employment. We compute the exposure variable at the beginning of the sample (year 1998), before the large increases in terms of trade experienced by the economy. The reason is to capture the effect of price changes and not the employment effect, and also we choose the year 1998 because metal-mining employment in 2003 could be determined, in part, by the commodity boom, generating endogenity. Indeed, it could be that firms in 2003 already were waiting the price shock and hired more workers. Then, choosing mining employment in 1998 we solve that problem. ε_{ct} is the error term.

One might think that, due to the shock is mostly exogenous, we could omit the term X_{ct} in the equation. But there would be problems associated to that equation, because it rest in the assumption that exposures of each municipality were randomly distributed. Indeed, it could be that municipalities with high metal-mining employment were already reducing their poverty rates faster that other municipalities. This is a possible source of endogenity, because changes in $\beta Log(P_t) \cdot \theta_{c,98}$ could be negatively correlated with unobservable trends of poverty reductions, and that would be positively biasing β. To solve this we add the covariates vector X_{ct} which includes control variables - explained in details latter - that previous literature indicated as important for explaining changes in poverty rates across regions[12].

This specification, by including county fixed-effects and year fixed-effects, allows as to control for county-specific variables that might affect poverty, and also for common time varying shocks affecting to all counties. In addition, the estimations include clustered errors for counties, for the case that errors aren't independently and identically distributed[13] across counties and time, or measurement problems in data. Thus, even though we are not able to identify the overall

[12] [McCaig, 2011] makes a detailed analysis of this problems, and he proposed two ways to solve this: (1) include covariates to control for unobservable trends, previous to the boom. And (2) use previous information to control for the unobservables trends - make a double difference in difference estimation -.

[13] This help us to have more reliable estimations if errors are auto-correlated in panel data.

impact of increases in metal prices during the period, we are able to identify the differential effect depending on whether a county is more dependent on metal minerals. This exposure is measured as the metal-mining employment share because our idea is that poverty effects of changes in terms of trade are mostly channeled through the labor market.

The expected sign of θ is negative, indicating that positive terms of trade shocks should reduce poverty, and in this case, the impact should be higher in more exposed counties. In fact, minor or zero effects should be expected in counties with no metal-mining activities. Our analysis is different from [Caselli and Michaels, 2009] who look at how oil windfalls across municipalities in Brazil have an impact on living standards, but the focus is on larger resources for municipalities. In the case of Chile, municipalities are not the main benefited by windfalls from mining because taxes from mining companies are collected by the central government. However, local governments may be indirectly benefited from the windfalls whether the central government transfers more resources to mining municipalities or through the increases of local revenues coming from the growing economic activity originated by the resources booms[14].

We use similar specification to look at the transmission mechanisms. In that estimations the variable y_{ct} will be the labor market outcomes: employment and wages. As we said, the most direct impact on labor markets of a positive terms of trade is an increase in labor demand, increasing wages and employment. Nevertheless, this positive shock may also have general equilibrium effects in several other dimensions. First, consider other complementary activities associated with the mining boom such as input providers or non-tradable services. In fact, commodity booms are commonly associated with, for example, construction booms that can increase activity and wages in those sectors. Then, our empirical exercises on the mechanisms estimates the impact of prices on wages and employment by other industries and workers skills.

In summary, up to now we have fourth different ways to take care of endogenity problems: First, almost all the commodity shock is exogenous; Second, we use a difference-in-difference

[14] Although this is an interesting possibility, we focus on the broad impact of price changes not distinguishing whether this was a direct effect on labor markets or indirect through increases in local government revenues.

analysis which allows as to control for county and year fixed effects; In third place we use the metal-mining employment share in 1998 as measure of exposure, to capture the effects of price changes and not the employment effects -the employment share in 2003 could be determined, in part, by the commodity shock-; and finally to solve the problem of unobservables trend correlated with the price change we include characteristics of municipalities for each year.

Finally, it could be that other variables or mechanisms were the real explanation of that bigger poverty reductions in metal-mining municipalities over the rest of them, instead of the commodity shock. We find 4 alternative economic reasons that could take part -maybe all- of the significance of our main variable, and we control for all of them. (i) *Trends*: Is possible that poverty is decreasing more in metal-mining municipalities because of unobservable trends, common within each type of municipalities. (ii) *Poverty Convergence*: It could be that that the *stedy stage* or the equilibrium poverty rate are lower for metal-mining counties, due to structural characteristics of those ones. (iii) *Plants Localization*: Maybe is more relevant the localization of production plants to explain the poverty reductions.(iv)*Political Economy*: This argument points to week institutions, political favors, and corruption, where is possible that the central government transfers more resources to metal-mining counties because these ones have Mayors with political interests, or because they are from the same coalition.

6 Empirical Results

In this section we present and analyze our empirical results. First we present our baseline results, then we analyze the fourth alternative explanations mentioned in the previous section, and finally we analyze the potential problems of a wrong measurement of poverty rates due to heterogeneity in the cost of living.

6.1 Baseline Results

Table 1 contains the four regressions of our baseline results of commodity shock over poverty rates, for the period of 1998 to 2013. The four regressions include county and year fixed effects. The first column is just for the shock, and then in columns to and three we controls: First the GDP growth of the Region which the municipality belongs, and in column 3 the typical controls: the average years of schooling, the size of the municipality (popullation), the average size of the households (N° of members), and the share of people living in urbane zones. Finally, in column four we restrict the estimation just to the repeated municipalities -presents in the seven years-, finding that the significance doesn't change and the effect is almost the same. All the results are significant at 95% of confidence. In column 4 we found our core result, where the *Beta* is -0.152[15]. But this coefficient doesn't have interpretation by its own, because it depends on the exposure level of municipalities and the standard deviation of the shock. The average standard deviation of the commodity shock was 0.70 approximately. Therefore, considering that standard deviation, for those municipalities that are in the median of the exposure level the shock reduce poverty rates -on average- in 0.48 percentge points (pp), for those in the 75th percentile the reduction was 1.08, for 95th percentile is was 2.39, and for the 99th percentile the poverty rate 3.62 percentage points due to the shock.

For example, municipalities *Diego de Almagro, Andacollo* and *Chañaral* have the highest levels of exposure and the estimations predicts that, on average, the poverty reductions due to the shock would be 3.62, 3.11, and 2.4 percentage points respectively. Obviously, municipalities with no exposure had no impact in their poverty rates due to the shock.

6.2 Alternative Explanations

These last results conform our baseline results, but there could be several reasons that may explain the bigger poverty reductions on metal-mining counties. Here we explore four alterna-

[15]This coefficient comes from $\frac{dPov_{ct}}{dLog(Index_t)} = \beta \cdot Exposure$

Commodity Shock over Poverty Rates [1998-2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-0.161**	-0.161**	-0.158**	-0.152**
	(0.065)	(0.065)	(0.066)	(0.066)
GDP growth (Region)	-	0.006	0.023	0.041
		(0.093)	(0.086)	(0.084)
Municipality Size	-	-	0.028	0.027
			(0.022)	(0.022)
Households Size	-	-	0.058**	0.040
			(0.025)	(0.025)
Schooling	-	-	-0.123***	-0.146***
			(0.038)	(0.039)
Urban Zone	-	-	0.063*	0.080**
			(0.036)	(0.037)
Constant	0.260***	0.260***	0.116	0.194
	(0.008)	(0.009)	(0.232)	(0.246)
Observations	1,356	1,356	1,356	1,274
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.353	0.353	0.369	0.392
Number of Municipalities	196	196	196	182

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 1

tive explanations for the reductions in poverty rates that could be distorting our identification strategy: Trends, Plants Location, Poverty Convergence, and Political Economy.

Trends

The validity of our empirical estimations and the identification strategy lies on the exogeneity of the commodity shock, and the heterogeneity of local impacts across municipalities. Thus, municipalities exposed to the shock had higher poverty rates reductions than others, due to the shock. But, also we could have a lucky issues in this story affecting the estimations. Suppose that, just for coincidence or luck, metal-mining counties were already reducing their poverty rates more than the others counties. This is a matter of trends, and it might affect our results decreasing the importance of the shock.

Trends and Commodity Shock over Poverty Rates
[1998-2013]

	(1)	(2)	(3)
Commodity Shock	-	-	-0.136**
			(0.068)
Trends (Metal-mining)	-0.014***	-0.012***	-0.010***
	(0.002)	(0.002)	(0.002)
Trends (Non Metal-mining)	-0.010***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
Controls	No	Yes	Yes
Observations	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes
R-squared	0.349	0.365	0.370
Number of Municipalities	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Note: The null hypothesis for the test of equal trends is rejected for the three regressions. The test for column (4) is rejected with a value of $Prob > F = 0.2264$.

Table 2

We create trends for both types of municipalities, and run the regressions. The results are presented in Table 2. Column 1 is a regression just for the trends without any controls, column 2 include our basic controls[16], and column 3 includes the commodity shock variable[17]. In all regressions both trends are negative and significant, and with higher magnitude for metal-mining municipalities. This mean that our intuition was right and counties exposed to the shock had higher trends in poverty reductions. But the commodity shock variable in column 4 is still significant, with a lower coefficient. Therefore, although trends explain a bit share of the poverty reductions, the commodity shock is still the main variable explaining the poverty rates reductions.

[16]Those used in Table 1, column 4.
[17]These three columns (regressions) are equal for the next alternative explanations and transmission mechanisms.

Plants Location

Our second alternative explanation refers to the location of the plants where metal ores are produced, in the sense that maybe we are measuring the exposure to the shock in a wrong way. It could be that the variable in CASEN that indicates where the individual lives presents mistakes - for instance, workers from Santiago that declares to live in Antofagasta because they work there and also live some days there -. Therefore, if our exposure variable is wrong, it should be measured in a different way: one possibility is the share of metal-minerals production of each county, but since we don't have that data we measure the exposure considering only if municipalities have plants producing cooper o not.

We create a dummy that takes value 1 if the municipality had at least one mining company producing cooper in 1998 and use that dummy as our new exposure variable, interacted with the Metals Price Index. In this analysis we use data from COCHILCO of the main cooper producer companies. Table 3 replicates our regressions showing that this concern is not justified. From the table we conclude that the new variable for the shock is not significant with and without controls, and in column 3 when we include the original variable for the commodity shock we find that the significance and magnitude is the same as without the Plants Location variable. This means that the results doesn't change at all if we include this new variable, therefore we exclude this variable in future estimations.

Poverty Convergence

Another major concern is the idea that this poverty reduction is just a matter of poverty convergence, and the shock is just a correlation. Indeed, this might be possible because, on average, in 1998 poverty for metal-mining counties was higher, as we saw in 1. As is common in the literature, we create a variable for the initial poverty - the poverty of each municipality in 1998 - to consider the convergence, and we interact that with the price index. Municipalities with higher initial poverty should have had higher reductions in poverty rate.

Plants Location and Commodity Shock over Pov. Rates
[1998-2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-	-	-0.153**	-0.133*
			(0.069)	(0.070)
Plants Location⋆Pindex	-0.015	-0.018	-0.003	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)
Trends (Metal-mining)	-	-	-	-0.010***
				(0.002)
Trends (Non Metal-mining)	-	-	-	-0.007***
				(0.002)
Controls	No	Yes	Yes	Yes
Observations	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.346	0.364	0.369	0.370
Number of Municipalities	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3

In Table 4 we again recreate the regressions including the initial poverty variable. From columns 1 to 3 we confirm our expectations: the initial poverty has a negative and significant effect over the poverty rate, which mean that counties with higher initial poverty had bigger poverty reductions. From column 3 we conclude that controlling for the initial poverty our commodity shock variable remains significant and with the same magnitude. Even including trends and initial poverty - column 4 - we found that the commodity shock is relevant explaining poverty reductions, as we expected, but with lower magnitude: the *Beta* coefficient is 0.124.

Political Economy

Our last possible explanation is a political economy argument to reduce poverty. One of our main assumptions in the empirical estimation is that fiscal revenues provided by mining companies are equally distributed across municipalities. But, there is not a clear way to corroborate that and it could happen that municipalities where the Mayor is from the same political side than

Initial Poverty and Commodity Shock over Pov. Rates
[1998-2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-	-	-0.153***	-0.124***
			(0.045)	(0.045)
Poverty98⋆Pindex	-0.218***	-0.210***	-0.209***	-0.211***
	(0.019)	(0.019)	(0.018)	(0.017)
Trends (Metal-mining)	-	-	-	0.002
				(0.002)
Trends (Non Metal-mining)	-	-	-	0.005***
				(0.002)
Controls	No	Yes	Yes	Yes
Observations	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.416	0.424	0.431	0.433
Number of Municipalities	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4

the incumbent government, they receive more resources than other municipalities. Therefore, if - by coincidence - metal-mining counties have more of those Mayors, then maybe they are receiving more resources from government and in that way reducing poverty.

Table 5 gives clear results. Variables MG_right and MG_left are dummies equal to one if both Mayor and Government are from the same side, right or left respectively, for each year. Then, variables $MG\_right \star Pindex$ and $MG\_left \star Pindex$ are interactions of MG_right and MG_left with our price index. None of these variables are significant in any of the regressions. Neither by themselves, or when we include controls. Also, in column four when we regress the commodity shock and all possible explanations, all variables of political economy are non significant. Due to these results we omit those variables in all next regressions, in the same way we omit the Plants Location variable.

Therefore, column 4 in table 4 is our main regression considering all basic controls, trends, and poverty convergence. This mean that municipalities that are in the median of the exposure

Political Economy and Commodity Shock over Pov. Rates
[1998-2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-	-	-0.158**	-0.129***
			(0.067)	(0.045)
Trends (Metal-mining)	-	-	-	0.002
				(0.002)
Trends (Non Metal-mining)	-	-	-	0.006***
				(0.002)
Poverty98⋆Pindex	-	-	-	-0.214***
				(0.018)
MG_right	0.003	0.001	-0.002	-0.010
	(0.007)	(0.008)	(0.008)	(0.007)
MG_left	0.001	0.003	0.004	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)
MG_right⋆Pindex	-	0.001	0.001	0.002
		(0.003)	(0.003)	(0.003)
MG_left⋆Pindex	-	0.002	0.000	0.000
		(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes
Observations	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared				
Number of Municipalities	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5

level the shock reduce poverty rates - on average - in 0.39 percentage points, for those in the 75th percentile the reduction was 0.88 pp, for 95th percentile is was 1.95 pp, and for the 99th percentile the poverty rate drop was 2.96 pp due to the boom.

6.3 Heterogeneity in the Cost of Living

The biggest problem of this investigation is that poverty rates could be higher than the data says. Up to now an individual is poor when their income is lower than a certain level independent of where he lives, but this measure has a huge problem: it ignores the difference in the cost of living across regions or municipalities. Our results might by over-estimated due to differences in the cost of living across municipalities. Indeed, if prices in metal-mining municipalities rises more than the rest, then the minimum income to overcome poverty would be higher in those municipalities. But we don't now this, because Chile doesn't have measures for municipal inflation rates or even for regions. We just have the *Consumers Price Index* (CPI) at a national level.

Solve that problem is very important if we want to find legitimate poverty reductions. One way is by analyzing the price evolution of nontradable goods or services, because they are the source of heterogeneity in cost of living[18]. [Aroca and Paredes, 2008] works in this idea creating a regional index for the cost of living. Following their idea we focus in the rental cost of apartments across municipalities for two analysis: (*i*) as a measure of cost of living: if rental cost takes an important share of families budgets, then that would be a good approximation to a measure of cost of living. And (*ii*) to create a *Municipal Consumers Price Index* (MCPI): The CPI is a national index, conformed by several components of goods and services. One of them is "Housing, Water, Electricity, Gas and other Fuels" where we argue that the main variation across municipalities of this item is the housing cost -rental cost of apartments-, due to water, electricity, gas and other fuels tends to be quite similar throughout the country. Given that, we create the MCPI changing this item with an index for the average rental cost of apartments and houses for each municipality in the period of 2000 to 2013 using CASEN's data.

For the first analysis we analyze the evolution of rental cost for metal-mining municipalities and non metal-mining municipalities. For the rental cost we consider the simple average for each

[18] Price of tradable goods are common for the whole country.

county and also we construct the Hedonic Prices for those apartments and houses[19]. Figure 6 shows the evolution between 2000 and 2013 - six CASEN's[20] - for the simple average (left) and the hedonic rental cost (right), weighted by population. The simple average rental cost rises more for metal-mining municipalities, but for the hedonic prices there is no significant difference between both types of counties. This should mean that indeed the rental cost increased more for metal-mining municipalities, but the reason was that new apartments and houses were constructed in better conditions, quality, or size. Therefore, this analysis says that the rental cost gap between both types of municipalities are explained for better structural characteristics of apartments and houses in metal-mining counties.

From the other side, the core of the second analysis is the construction of Consumers Prices Index for each municipality (MCPI) where the source of heterogeneity comes from the rental cost of apartments and houses. Table A4 in Appendix 11 shows the evolution of several index variables. The first and second columns are the national CPI and an index for the average rental cost - using simple average rental cost, not hedonic prices - reconstructed to be 100 in 2003; columns 3 and 4 are the rental cost for metal and non-metal mining counties; columns 5 to 8 are Municipal Consumers Price Index for both type of municipalities under two different measures: MCPI [1] is the index when the weighting factor for the Rental Cost Index is approximately 4% which is the weight just for the rental prices in the basket of the CPI. MCPI [2] assumes that all non-tradable goods moves similar to the rental prices, so the weighting factor rises to almost 40%. The last two columns are the wages for metal and non-metal mining counties.

The last row of the table is the change (%) for each variable between 2000 and 2013. We

[19]The Hedonic prices are constructed by a linear regression of the declared rental cost against characteristic of the house - number of rooms, bathrooms, living rooms, and others -, quality of the house - measured by the pollster criterion -, geographic zone where the house is located, and the regional quartile of income - capturing the quality of the sector where is located -. We also clean the outliers, which are those who declare a rental cost of more than $3 millions *pesos*.

[20]There is no data for 1998

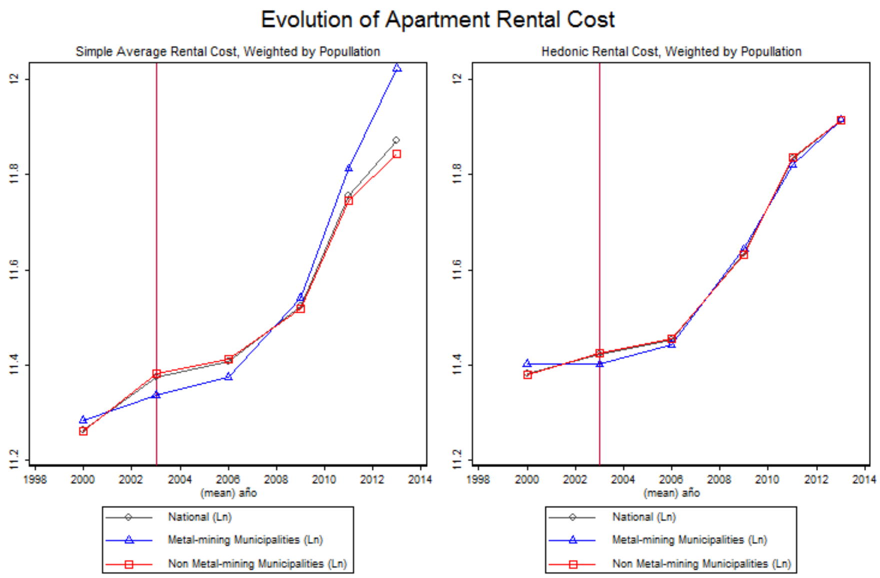

Figure 6

can notice that for metal-mining counties the changes in rental cost, MCPI [1], and MCPI [2] are higher than for non-metal counties. That can mitigate the magnitude and/or also the significance of our previous results. But, also wages in metal-mining counties grow almost double than non metal-mining ones. Hence, as we are interested in the differences between both types of municipalities, we can calculate the differences on wage growth over differences in MCPI growth[21]. Taking MCPI [1] we find that difference in wages growth are nine times the difference between municipal consumers price index; and taking MCPI [2] the ratio falls to almost 1[22]. A graphical way to see this is by looking Figures 9 and 10 that shows the evolution of wages for municipalities and the MCPI [1], where wages are measured as the median and average respectively. Wages growth significantly more for metal-mining municipalities, while

[21] That means that we calculate $\lambda = \dfrac{WG^{mc} - WG^{nmc}}{MCPI^{mc} - MCPI^{nmc}}$, where WG^{mc} and WG^{nmc} are the wage growth for metal-mining and non metal-mining counties.

[22] Falls to 0.91 to be exactly.

the cost of life of those municipalities remains very close to non metal-mining ones.

With the information of the Hedonic prices evolution and the MCPI analysis, we believe that although prices - the cost of living - grew faster for metal-mining municipalities it doesn't look like a problem for the conclusions, since the price evolution is apparently explained by better characteristics of houses, and wages also grew faster for those municipalities. Assuming a strong unfavorable scenario (MCPI [2]) it's not clear that those results would affect significantly our estimations.

7 Transmission Mechanisms

Now that we are clear that the commodity shock had a significant impact in poverty rates reductions for municipalities exposed to the shock, we proceed to analyze the transmission mechanisms behind the effect. Our belief is that the labor market is the most important channel where the commodity shock was transmitted, so we evaluate the impact over employment and wages. Employment is measured as percentage over total county employment, and wages as the simple average in logarithm. We also differentiate workers between skilled and unskilled, according to their educational level. In this investigation workers are defined as skilled if they have some post-secondary education -complete or incomplete-, and unskilled if they have at most secondary education. In addition, we include in the regressions the variables used for the alternative explanations, because they can also affect our labor market variables.

Employment

As we said before, for all regressions tables in this section columns 1-3 indicates the same. Column 1 is a regression for the shock without any control variables; column 2 adds the basic control variables - those used in table 1 -; and finally column 3 adds the control variables selected in the alternative explanations - trends and poverty convergence -. We prefer column 3 as our main regressions. Table 6 present a positive and significant - at 95% - effect of the shock over total employment rate in municipalities, where the beta coefficient is 0.06. That magnitude mean that for municipalities with exposure values in the median, and percentiles 75, 95 and 99 had on average an increase in total employment of 0.19, 0.43, 0.96, and 1.45 percentage points respectively, considering the average standard deviation of the shock.

Commodity Shock over Total Employment rate

[1998-2013]

	(1)	(2)	(3)
Commodity Shock	0.047**	0.052**	0.061***
	(0.022)	(0.022)	(0.023)
Trends (Metal-mining)			0.006***
			(0.001)
Trends (Non Metal-mining)			0.007***
			(0.001)
Controls	No	Yes	Yes
Observations	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes
R-squared	0.309	0.322	0.323
Number of Municipalities	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6

Table 7 separates employment between metal-mining and non metal-mining employment rates. This table shows that the shock increases the total employment mainly due to metal-mining employment, but there is negative or not significant effect over non metal-mining employment. The effect is significant at 99% of confidence, with a coefficient of 0.082.

The shock had a significant impact over employment, mainly due to increase in metal-mining workers. But, still we don't now what type of workers were hiring mining firms. Table 8 shows the impact of shock over skilled and unskilled employment rate, and Table 9 evaluates the same but just for metal-mining workers. This two tables indicates that the commodity shock induce firms to hire more unskilled workers, while to skilled workers the effect is not significant; and also that within metal-mining industry there is a significant increase in unskilled workers, but not to the skilled ones. In particular, the beta coefficient for the commodity shock variable over

Commodity Shock over Metal and Non-Metal Employment rates [1998-2013]

	Metal Empl. rate			Non-Metal Empl. rate		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.090***	0.091***	0.082***	-0.043**	-0.039*	-0.022
	(0.020)	(0.018)	(0.019)	(0.021)	(0.022)	(0.024)
Trends (Metal-mining)			0.001***			0.004***
			(0.000)			(0.001)
Trends (Non Metal-mining)			0.001***			0.006***
			(0.000)			(0.001)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.290	0.296	0.305	0.227	0.240	0.244
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7

unskilled metal mining employment rate is 0.067, which mean that for metal-mining counties in median and percentiles 75, 95 and 99 of the exposure level the shock increases, on average, unskilled employment in 0.22, 0.48, 1.07, and 1.62 percentage points respectively, according to the average standard deviation.

Wages

Our final analysis in this section is about wages: the second transmission mechanisms. The commodity shock should had a significant impact in unskilled workers wages due to the increase in the demand of those workers in the mining industry -and probably in other sectors too-. One important issue is how we define the wages for each municipality. Here we use total wages, skilled workers wages and unskilled workers wages, and each one of them can be defined in two different ways: As an average, or as the median. In our estimations we use both, and we'll see that the results doesn't change.

Table 10 shows our main regressions over average and median total wages. There is a

Commodity Shock over Skilled and Unskilled Employment rates [1998-2013]

	Skilled Empl. rate			**Unskilled Empl. rate**		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.004	0.007	0.014	0.043*	0.044*	0.047*
	(0.015)	(0.016)	(0.016)	(0.023)	(0.023)	(0.025)
Trends (Metal-mining)			0.001			0.005***
			(0.001)			(0.001)
Trends (Non Metal-mining)			0.001			0.006***
			(0.001)			(0.001)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.224	0.302	0.303	0.318	0.344	0.344
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8

Commodity Shock over Skilled and Unskilled Metal-Mining Empl. rates [1998-2013]

	Skilled Metal-Mining Empl. Rate			**Unskilled Metal-Mining Empl. Rate**		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.013	0.013	0.013	0.086***	0.083***	0.068***
	(0.011)	(0.010)	(0.010)	(0.023)	(0.023)	(0.024)
Trends (Metal-mining)			0.000***			0.001
			(0.000)			(0.001)
Trends (Non Metal-mining)			0.000***			-0.001
			(0.000)			(0.001)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.082	0.109	0.109	0.206	0.273	0.277
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9

significant impact over total wages, both measured as average or median. From column 3 we found that the beta coefficients for the commodity shock are quite similar for both average and median wages. For the exposure level in the median, and percentiles 75, 95 and 99 the shock, on average, increases total median wages in 1.48%, 3.32%, 7.35%, and 11.13% respectively.

Commodity Shock over Total Average and Median Wages [1998-2013]

	Total Average Wages (Ln)			Total Median Wages (Ln)		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.618***	0.513***	0.449**	0.501***	0.488***	0.467***
	(0.166)	(0.167)	(0.176)	(0.088)	(0.084)	(0.089)
Trends (Metal-mining)			0.058***			0.114***
			(0.005)			(0.003)
Trends (Non Metal-mining)			0.051***			0.112***
			(0.004)			(0.003)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.565	0.609	0.610	0.920	0.927	0.927
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 10

Now, exploring deeper into the transmission mechanisms we distinct wages between skilled and unskilled workers according to our previous definition. Table 11 are the results for the regressions of the shock over skilled workers wages. As we expected there is no significant impact of the boom on skilled workers wages - both to average or median measures - in any of the regressions. Therefore, the significant impact over total wages must be explained for the changes in unskilled workers wages due to the shock.

Table 12 corroborates that the commodity shock had a big and significant effect in unskilled workers wages, proving that total wages grow up mainly to increases in unskilled workers wages due to the commodity shock, independently . Column 3 shows that an increase in the average standard deviation of the commodity shock rises unskilled workers wages in 1.35% for counties in the median of the exposure level; and for the counties in percentiles 75, 95 and 99 the impact was 3.02%, 6.69% and 10.13% respectively. This results mean that the increase in total wages for municipalities are mainly driven by changes in wages of unskilled workers, which is concordant with the preliminary evidence founded in Section 3.4 for the evolution of wages.

Finally Table 13 present a summary table of the average effects over poverty and the main

Commodity Shock over Average and Median Wages for Skilled Workers [1998-2013]

	Skilled Average Wages (Ln)			Skilled Median Wages (Ln)		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.247	0.127	0.139	0.193	0.103	0.135
	(0.220)	(0.239)	(0.257)	(0.161)	(0.164)	(0.184)
Trends (Metal-mining)			0.105***			0.136***
			(0.007)			(0.007)
Trends (Non Metal-mining)			0.107***			0.140***
			(0.008)			(0.006)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,352	1,352	1,352	1,352	1,352	1,352
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.546	0.576	0.576	0.690	0.708	0.708
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 11

Commodity Shock over Average and Median Wages for Unskilled Workers [1998-2013]

	Unskilled Average Wages (Ln)			Unskilled Median Wages (Ln)		
	(1)	(2)	(3)	(1)	(2)	(3)
Commodity Shock	0.605***	0.562***	0.480***	0.471***	0.456***	0.425***
	(0.083)	(0.075)	(0.075)	(0.089)	(0.088)	(0.092)
Trends (Metal-mining)			0.081***			0.113***
			(0.004)			(0.003)
Trends (Non Metal-mining)			0.072***			0.110***
			(0.004)			(0.003)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.824	0.832	0.833	0.929	0.932	0.932
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 12

transmission mechanisms for exposed municipalities situated in the median and percentiles 75, 95 and 99 of the exposure variable. Is important to notice that effects vary widely between those groups of municipalities. Effect on poverty rates - column 2 - for counties within percentile 95 are more than 2 times higher than percentile 75, and also those in percentile 75 are more than

2 times higher than counties in the median. This is explained by big differences in the average exposure level of those percentiles. In addition, Figure 8 in Appendix 10 shows the evolution for the weighted average poverty rates for municipalities over and below percentile 75 of exposure level[23]. Municipalities in or above the 75th percentile have, on average, lower poverty rate after the shock and higher reductions. Also, the gap in poverty rates between both groups remains relatively constant for years after the boom.

Commodity Shock average impacts* over main variables - Exposed Counties

Exposure Level	Poverty (1)	Poverty (2)	Total Employment	Unskilled Metal Empl. Rate	Total Median Wages (%)	Unskilled Median Wages (%)
Median (4.5%)	-0.48	-0.39	0.19	0.22	1.48	1.35
75th Percentile (10.1%)	-1.08	-0.88	0.43	0.48	3.32	3.02
95th Percentile (22.4%)	-2.39	-1.95	0.96	1.07	7.35	6.69
99th Percentile (33.9%)	-3.62	-2.96	1.45	1.62	11.13	10.13
Simple Average (7.9%)	-0.84	-0.68	0.34	0.45	2.58	2.35

(*) These impacts are considering the average standard deviation for the seven years analyzed, equal to 0.7014, which means that these are average impacts between surveyed years, for the sample period.

Poverty (1) is the impact over poverty when we control just for basic controls. The coefficient is -0.152, presented in Table 2. Poverty (2) is the impact over poverty when we control for all controls -including trends and initial poverty-. The coefficient is -0.124, presented in Table 4.

Impacts on poverty and employment are in percentage points instead of a percentage changes, due to our econometric model where we estimates impacts over the difference in rates. Wages are measured in *Log*, therefore effects are in percentage changes.

Table 13

These effects are for exposed municipalities, therefore excluding counties with metal-mining employment share below to 1%. Table 14 in Appendix, shows these effects but considering all counties, which mean that the exposure level for each percentile is lower, and hence effects also decrease.

[23] Of the 50 municipalities exposed to the shock, exactly the half are above and below the 75th percentile.

8 Robustness Check

Once we have our main results and checking that the significance and intensity of the shock survive to several controls, we proceed to show some robustness checks to complement our analysis. The tables to which we refer in this section are presented in Appendix II. In first place we make a *falsification analysis* to evaluate the possibility of a spurious regression. To do that we regress our main variable with poverty rate of the previous period -poverty lag-. The logic is that the commodity shock should affect poverty rates in the same period or the followers but not the previous ones, and that poverty lag is very correlated with actual poverty. The results are presented in Table 15. Indeed, the commodity shock doesn't have significant impact over poverty lag, which makes sense with our hypothesis of a causal relationship between the shock and poverty rates.

Second we restrict our sample in three ways: (*i*) Excluding the Metropolitan Region (MR) because there is located the country-capital -*Santiago*- that is the largest city in terms of population and GDP. The reason is that the characteristics of the MR could be distorting the results, due to it's size. The results of this concerns are presented in Table 16 where the results remains their consistency. The effect over poverty is still significant, but with lower impact, which mean that these effect occurs despite of excluding the biggest region in our sample. (*ii*) We take the period from 1998 to 2009, because the CASEN's methodological documents of 2011 and 2013 recommends not to use the municipal expansion factors. For those year the survey's implementation changes and maybe data are not representative at a municipal level. We didn't consider this concern in our main analysis because those are not problem to our specific methodology. Representation problems would arrive if we tried to obtain conclusions for municipalities using data at individual level, but since we use aggregated data there is no problem using CASEN's for those years. Nevertheless, to dispel doubts we take account this issue in the robustness check. In Table 17 we notice that the results over poverty rates and the transmission mechanisms doesn't change restricting the sample, but the coefficient of the shock is lower.

(iii) We restrict the sample just to the repeated municipalities. This mean that our data is reduced to 1264 observations of 182 municipalities. It could be that municipalities that are not repeated in all seven waves were distorting our estimations -acting as outliers-, or maybe just because that municipalities had bigger poverty rates reduction in those years, as a matter of coincidence. This robustness check consider that possibility and the results are exposed in Tables 18 and 19. The effect over poverty rates is still significant - the impact remains significant at 95% but coefficient decrease to 0.114, slightly smaller than the previous ones - and the relevant transmission mechanisms in labor market are the same: firms hire more unskilled workers and that rises their wages.

Then, our third robustness check - and one of the most important - is that maybe other commodities that also experiment larger booms explain movements in poverty rates, wages and employment. We construct a second index variable for the most relevant commodities different to metal-mining ones, called *Other Commodities*, defining a product as relevant if the exports value in 2003 accounts more than 1% over all products. Using data from the The Observatory of Economic Complexity and the Central Bank of Chile (CBCh) we find that those commodities are: Grapes, Wine, Apples, Fruits in general, Fish (specifically Salmon and Trout), Cellulose, some Alcohols and Lubricating petroleum oils. The last two are the less relevant, and we don't have price data for them but for all other products we have price index and value of exports from the CBCh -or some aggregation of the products-, for all the sample period. This variable is constructed in exactly the same way than the Metal's Price Index, where the weight for each product is the value of exports in 1998 over the total sum.

Therefore, now we estimates $y_{c,t} = \alpha_c + \alpha_t + \beta_1 Log(P_t) \cdot \theta_{c,98} + \beta_2 Log(P_t^{oc}) \cdot \vartheta_{c,98} + \lambda' X_{c,t} + \varepsilon_{c,t}$, where $\vartheta_{c,98}$ and $Log(P_t^{oc})$ are the exposure level for counties intensive in these other relevant commodities, and the price index for the new products respectively. In Table 20 we present the results from estimations, finding that the *Others Commodities* variable is not relevant to explain poverty reductions when we include Trends and Initial Poverty, and our main variable is still significant in both cases and for the transmission mechanisms. Also, the new variable is significant explaining reductions in skilled employment, rises in unskilled metal-mining employment, and increases in total, skilled and unskilled wages.

In fourth place we change our measure of poverty from an absolute measurement to a relative one. Indeed, some countries authorities uses relative poverty measurements in order to include some inequality criterion. Therefore, following [Foster, 2016] we said that households are relatively poor if their total income - including subsidies and government transfers - are below to the median of all households in the municipality, to the 50% of the median, and also to the average of all households. Data shows a clear divergence in the relative poverty rate path for exposed and non-exposed counties, as it can be notice in Figure 11[24]. Results are presented in Table 21 and it shows that the commodity shock had a significant impact on relative poverty rates for exposed municipalities both when the threshold is the average, the median, and the 50% of the median of all households -columns 1, 2, and 3 respectively-.

In addition, we made a sensibility analysis checking if our estimations survive to some changes in the exposure level. In particular, the results are the same if we change our exposure measure to metal-mining employment share in 2000 -excluding year 1998- or the average from 1998 and 2000. Table 22 shows this estimations on poverty: column 1 is when we use year 2000 for the exposure variable, and column 2 is for the average between 1998 and 2000.

The fifth check is about migration. The results may be overestimated if migration across municipalities explain a share of the differences in poverty reduction, in particular if poor people move from metal-mining counties to other counties. Our belief is that the relationship is the contrary, mostly because if poor people had to move they would do it searching employment opportunities, and metal-mining counties seems to be the best option -in a commodity price boom context-. The problem is that we only have migration data from 2006-2013 in CASEN's[25], but taking that data we repeat our main estimations excluding those counties with high average migration rates for those years. The results are presented in Table 23, where in column 1 we

[24] The graph if for relative poverty when household income is below the median of all households in the county.

[25] In the surveys the question is: *¿where do you lived 5 year ago?*.

exclude counties above the 95th percentile of the average migration rate distribution, and column 2 and 3 are excluding those above the 90th and 75th percentiles. The commodity shock remains negative and significant, but with smaller magnitude. Therefore, migration across municipalities appears not to be a problem.

From the side of the transmission mechanisms, there may be other ways in which the shock is transmitted to affect poverty rates and that's about our seventh and eighth robustness analysis discusses. The seventh check is about Dutch Disease, where the metal's boom could affect wages and employment is several related industries, generating reallocation of employment or discouraging industries - commonly manufacturing -, and therefore decreasing the impact over poverty. Usually in literature of dutch disease the core analysis is over manufacturing industry, mostly because economic theory predicts that manufacturing is crucial in the country economic development and a drop of the exchange rate should deteriorate the industry, and therefore affecting the long term growth. But, interestingly, in Table 24 it can be seen that there is no significant effect over employment in manufacturing industry, but there is a negative and significant impact in electricity, construction, and finance industries[26]. Nevertheless, despite these findings it's possible that the commodity shock where less relevant -or even had a positive impact- on poverty for counties that are intensive both in metal-mining and manufacturing. Therefore, we include a new variable for counties intensives in both industries, interacted by the metal's price index[27], expecting a negative impact on poverty rates. Table 27 present the estimations, where including or not Trends and Poverty Convergence the effect on poverty is positive but not significant, and our main variable remains significant. With these two analysis we find no evidence of dutch disease affecting positively the poverty rates in counties exposed

[26] Also Table 25 shows that the commodity shock had a positive and significant effect in wages for most industries, including manufacturing, although wages is not a common variable to analyze dutch disease.

[27] Thus, the estimation was $y_{c,t} = \alpha_c + \alpha_t + \beta_1 Log(P_t) \cdot \theta^{m}_{c,98} + \beta_2 Log(P_t) \cdot \theta^{m,m}_{c,98} + \lambda' X_{c,t} + \varepsilon_{c,t}$, where $\theta^{m,m}_{c,98}$ is the exposure level in 1998 of counties intensives in metal-mining and manufacturing. We have 11 counties intensives in both industries.

to the shock.

Finally, our eighth and last robustness check is about female employment. The commodity shock could increase the demand of female employment in several industries, therefore helping to reduce poverty, mostly if female employment was low before the shock. Table 26 shows the effect over total female employment, and also by industries. There is no significant effect in total female employment, but a positive and significant effect in mining industry and negative in agriculture and finance. Apparently, the shock just produced a reallocation of females across industries, without affecting total employment[28].

9 Conclusion and Discussion

In this work we explore the local economic effects on poverty rates of the exogenous commodity shock - mainly due to China's huge demand of commodities -, and also the main labor market transmission mechanisms driving the poverty reductions. Using CASEN data at a municipal level for seven years we estimates a differences-in-differences equation, where the main variable is a price index that exploits the heterogeneity in the level of exposure to the shock of each municipality - measured as the share of metal-mining workers -. Then the effects over counties poverty rates depends on the level of exposure of each one. Also, our identification strategy have different ways to solve possible endogeneity problems: the external shock is exogenous, include county and year fixed effects, we use the metal-mining share of employment in 1998 as measure of exposure, and controls for aggregate socioeconomic characteristics of municipalities.

The results shows that there is a significant and negative impact on poverty rates. The magnitude of the reductions are higher when the exposure level is higher too. Moreover, the significance remains even if we control for two relevant alternative explanations supported by the economic theory: trends and poverty convergence - the location of where metals are produced

[28]Interestingly, the variable for other relevant commodities has a positive and significant impact on female employment, driven by manufacturing and services industries.

or a political economic analysis are not relevant -. In particular we find that metal-mining municipalities, on average, reduces their poverty rates in a range of 0.39 to 2.96 percentage points more than non metal-mining ones, depending of the exposure levels.

About the labor market transmission mechanisms we find that the commodity shock increases the demand for unskilled workers in the metal-mining industry and also the wages for unskilled workers. The reason is that the metal-mining industry is intensive in unskilled workers, so the commodity shock increases the firm's demand for those workers generating employment and wages growth. In that way, those workers could overcome poverty. In concrete, the estimations shows that, depending in the exposure level, the shock increases unskilled metal-mining employment share in a range of 0.22 to 1.62 percentage points more than non exposed counties, and unskilled wages in a range between 1.35% to 10.13%.

In Section 8 we implement several robustness checks to support our previous results. The results shows that we are not in presence of spurious regressions; also making several sample restrictions - to exclude possible outliers and representation problems - the estimations doesn't change in terms of significance; that including the impact of others relevant commodities our variable for the metal commodities shock is still significant; also changing the measurement of poverty rates to several relative poverty measures the impact remains significant; also selecting year 2000 or both 1998 and 2000 to define the exposure level to the shock we find significant effects on poverty rates; and finally we can said that we don't find evidence of dutch disease, either female employment, as transmission mechanisms of the shock.

We go forward deeply to solve probably our biggest problem in this investigation: the possibility of different cost of living across municipalities, that could be underestimating the poverty rates - or overestimating real wages -. Under two analysis we conclude that this doesn't seems to be a problem. The Hedonic prices analysis shows that rental cost of apartments and houses is similar between municipalities when we control for the characteristics of those. From other side, the construction of a Municipal Consumers Price index is a interesting and intuitive way to analyze this problem, and the resulting tables are not conclusive about the difference in wages and MCPI growth under an unfavorable scenario. This is a new step in the important issue of heterogeneity in the cost of living and the necessity of a less aggregate measure of prices evolution, specially in country's with complicated geographies like Chile.

Indeed, future investigations can perform the way to solve this latter problem, although we think the analysis done in our work is enough to support the main findings. In addition, this work omits the possibility of spillovers between municipalities where good administration and performance of counties can affect positively to their neighbors. Also, if workers moves between close municipalities then their spending will be distributed among those municipalities. Other further investigations can analyze the dynamics of poverty rates reductions: graph 1 shows that, apparently, the biggest reductions were in the first years after the boom. Moreover, future research can deepen in possible indirect effects on poverty due to other industries growth - mining boom may affect positively other industries -. Than can help as to understand better the effects of the commodity shock over poverty rates.

Finally, although we use relative poverty rate to extend the definition and measurement for poor people, and to include some criterion of inequality, future research may deepen in this point by using multidimensional poverty rate at county level. That measurement include other dimensions: education, health, and housing and environment. It could be that commodity shocks don't had effects on those dimensions, but only in income and employment, and therefore the shock is less relevant for a multidimensional measurement of poverty. This may be a way to analyze if the shock had structural effects on poverty, or poverty rates will fluctuate according to commodities windfalls.

References

[Allcott and Keniston, 2014] Allcott, H. and Keniston, D. (2014). Dutch disease or agglomeration? the local economic effects of natual resource booms in modern america. *Cambridge, National Bureau of Economic Research.*

[Aragon et al., 2015] Aragon, F. M., Chuhan-Pole, P., and Land, B. C. (2015). The local economic impacts of resource abundance: What have we learned? *World Bank Group, Africa Region.*

[Aroca and Paredes, 2008] Aroca, P. and Paredes, D. (2008). Metodología para estimar un indice regional de costo de vivienda en chile. *Cuadernos de Economía, Vol. 45 (Mayo), pp. 129-143.*

[Baffes and Haniotis, 2010] Baffes, J. and Haniotis, T. (2010). Placing the 2006-08 commodity price boom into perspective. *World Bank Policy Research Working Paper No. 537.*

[Caselli and Michaels, 2009] Caselli, F. and Michaels, G. (2009). Do oil windfalls improve living standars? evidence from brazil. *Cambridge, National Bureau Of Economic Research.*

[COCHILCO, 2014] COCHILCO (2014). Yearbook: Copper and other mineral statistics. Technical report, Chilean Cooper Commission.

[Corden, 1984] Corden, W. M. (1984). Booming sector and dutch disease economics: Survey and consolidation. *Oxford Economic Papers pp. 359-380.*

[Edmonds et al., 2010] Edmonds, E. V., Pavcnik, N., and Topalova, P. (2010). Trade adjustment and human capital investments: Evidence from indian tariff reform. *American Economic Journal.*

[Erten and Ocampo, 2013] Erten, B. and Ocampo, J. A. (2013). Super cycles of commodity prices since the mid-nineteenth century. *World Development 44(1), 14-30.*

[Farooki and Kaplinsky, 2013] Farooki, M. and Kaplinsky, R. (2013). The impact of china on global commodity prices: the global reshaping of the resource sector (vol. 57). *Routledge Studies in Global Competition.*

[Foster, 2016] Foster, J. E. (2016). Absolute versus relative poverty. *The American Economic Review, Vol. 88, No. 2.*

[Gregorio, 2014] Gregorio, J. D. (2014). How latin america weathered the global financial crisis. *Peterson Institute for International Economics.*

[Howie and Atakhanova, 2014] Howie, P. and Atakhanova, Z. (2014). Resource boom and inequality: Kazakhstan as a case study. *Resources Policy, 39, 71-79.*

[i Martin and Subramanian, 2003] i Martin, X. S. and Subramanian, A. (2003). Addressing the natural resource curse: An illustration from nigeria. *Cambridge, National Bureau Of Economic Research.*

[Krugman, 1987] 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. *Journal of Development Economics 27(1-2): 41-55.*

[Krugman et al., 2006] Krugman, P., Obstfeld, M., and Melitz, M. (2006). Economía internacional: Teoría y políticas. *Pearson Educación S.A.*

[Marchand, 2014] Marchand, J. (2014). The distributional impacts of an energy boom in western canada. *Working paper (No. 2013-13), University of Alberta.*

[McCaig, 2011] McCaig, B. (2011). Exporting out of poverty: Provincial poverty in vietnam and u.s. market access. *Australia, Journal of International Economics.*

[McCaig and Pavcnik, 2014] McCaig, B. and Pavcnik, N. (2014). Export markets and labor allocation in a low-income country. *(No. w20455) National Bureau of Economic Research.*

[Mehlum et al., 2006] Mehlum, H., Moene, K., and Torvik, R. (2006). Institutions and the resource curse. *Economic Journal, 116(508), 1?20.*

[Ploeg, 2011] Ploeg, F. V. D. (2011). Natural resources: Curse or blessing? *Journal of Economic Perspectives, 49(2): 366-420.*

[Robinson et al., 2006] Robinson, J. A., Torvik, R., and Verdier, T. (2006). Political foundations of the resource curse. *Journal of Development Economics 79 (2): 447?468.*

[Sachs and Warner, 1995] Sachs, J. D. and Warner, A. M. (1995). Naturale resource abundance and economic growth. *Cambridge, National Bureau of Economic Research.*

[Sachs and Warner, 1999] Sachs, J. D. and Warner, A. M. (1999). The big push, natural resource booms and growth. *Journal of Development Economics, 59(1), 43-76.*

[Sachs and Warner, 2001] Sachs, J. D. and Warner, A. M. (2001). The curse of natural resources. *European Economic Review, 45(4?6), 827?838.*

[Sokoloff and Engerman, 2000] Sokoloff, K. L. and Engerman, S. L. (2000). History lessons: Institutions, factors endowments, and paths of development in the new world. *Journal of Economic Perspectives-Volume 14, Number 3-Pages 217-232.*

[Topalova, 2010] Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics.*

[Yu, 2011] Yu, Y. (2011). Identifying the linkages between major mining commodity prices and china?s economic growth?implications for latin america. *IMF Working Paper 11/86.*

10 Appendix I: Figures

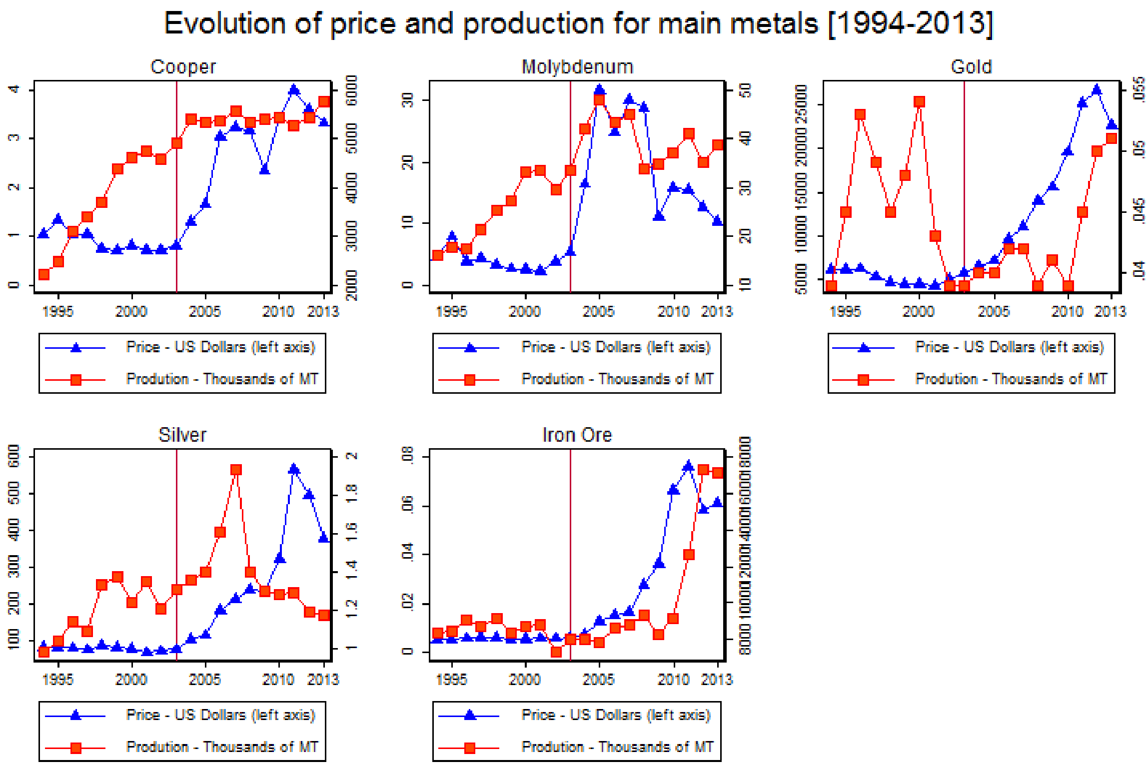

Figure 7

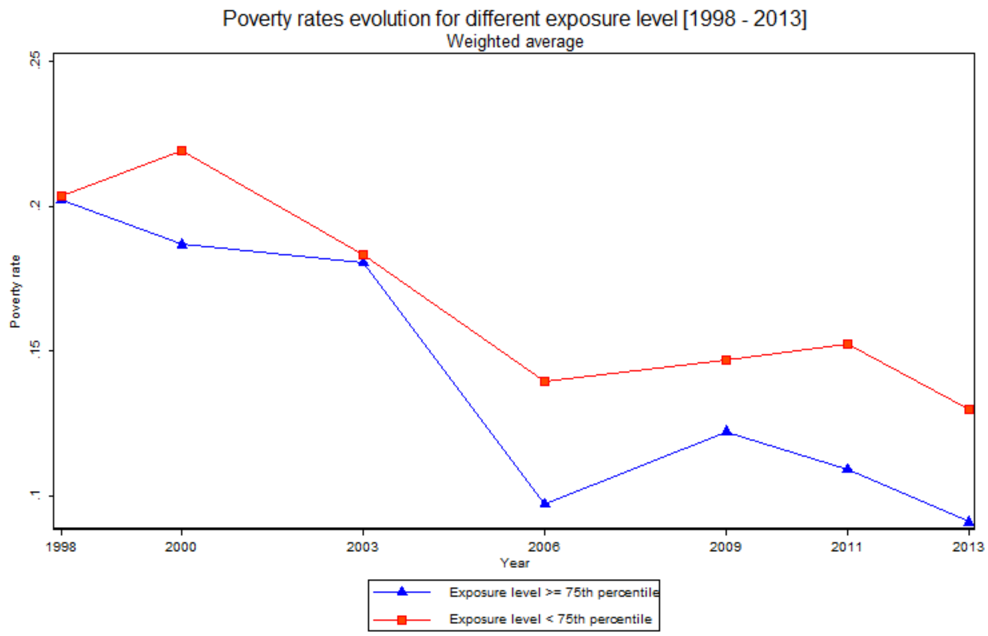

Figure 8

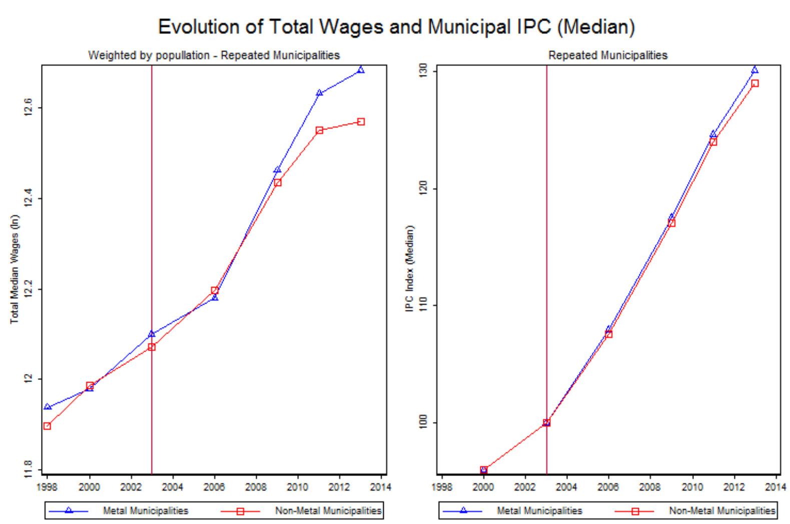

Figure 9

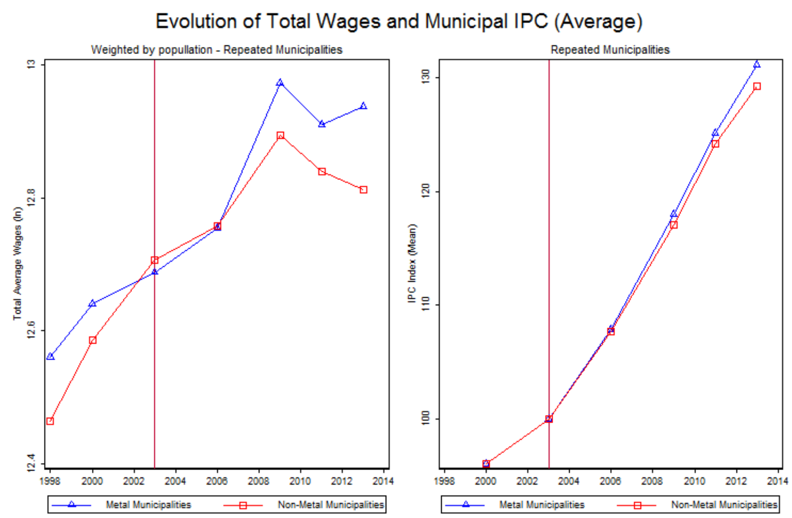

Figure 10

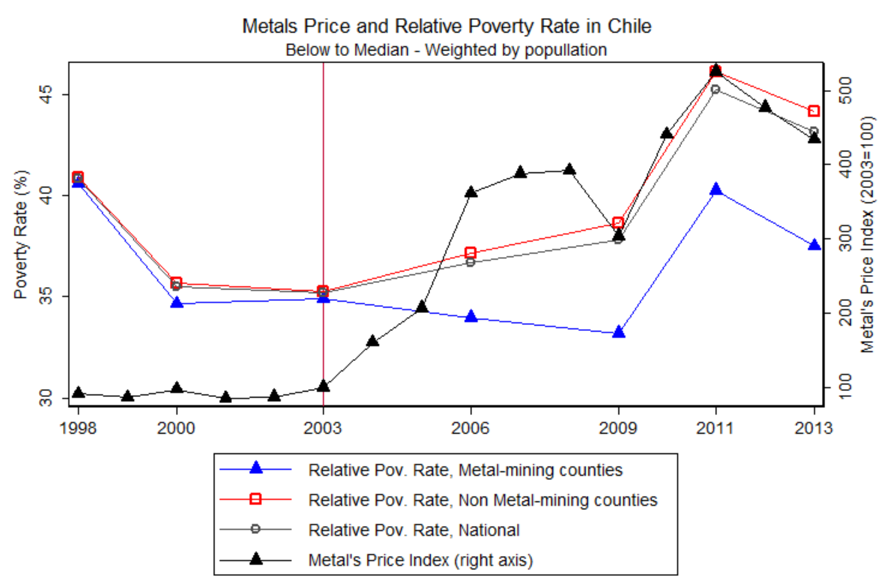

Figure 11

11 Appendix II: Tables

Commodity Shock average impacts* over main variables - All Counties

Exposure Level	Poverty (1)	Poverty (2)	Total Employment	Unskilled Metal Empl. Rate	Total Median Wages (%)	Unskilled Median Wages (%)
Median (0.2%)	-0.02	-0.01	0.01	0.01	0.01	0.05
75th Percentile (1.1%)	-0.12	-0.10	0.05	0.07	0.05	0.38
95th Percentile (15.7%)	-1.68	-1.37	0.67	0.90	0.75	5.15
99th Percentile (29.2%)	-3.11	-2.54	1.25	1.68	1.39	9.57
Simple Average (2.2%)	-0.23	-0.19	0.09	0.12	0.10	0.70

(*) These impacts are considering the average standard deviation for the seven years analyzed, equal to 0.7014, which means that these are average impacts between surveyed years, for the sample period.

Poverty (1) is the impact over poverty when we control just for basic controls. The coefficient is -0.152, presented in Table 2. Poverty (2) is the impact over poverty when we control for all controls -including trends and initial poverty-. The coefficient is -0.124, presented in Table 4.

Impacts on poverty and employment are in percentage points instead of a percentage changes, due to our econometric model where we estimates impacts over the difference in rates. Wages are measured in *Log*, therefore effects are in percentage changes.

Table 14

Falsification Test, effect over poverty lag [1998 - 2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-0.088	-0.085	-0.046	-0.041
	(0.054)	(0.058)	(0.042)	(0.042)
Trends (Metal-mining) - Lag	-	-	0.002	0.002
			(0.002)	(0.002)
Trends (Non Metal-mining) - Lag	-	-	0.007***	0.007***
			(0.002)	(0.002)
Poverty98⋆Pindex - Lag	-	-	-0.224***	-0.233***
			(0.019)	(0.019)
Controls - Lag	No	Yes	Yes	Yes
Observations	1,148	1,148	1,138	1,082
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.415	0.446	0.523	0.551
Number of Municipalities	196	196	195	181

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: The only variable for period t is the commodity shock. The dependent variable and all controls are in t-1. Also, if the controls are for period t, the results are the same.

Table 15

Effect over poverty rates, Excluding Metropolitan Regio (MR) [1998 - 2013]

	(1)	(2)	(3)	(4)
Commodity Shock	-0.123*	-0.114*	-0.109**	-0.108**
	(0.066)	(0.066)	(0.048)	(0.048)
Trends (Metal-mining)	-	-	0.002	0.002
			(0.002)	(0.002)
Trends (Non Metal-mining)	-	-	0.008***	0.008***
			(0.002)	(0.002)
Poverty98⋆Pindex	-	-	-0.199***	-0.207***
			(0.022)	(0.023)
Controls	No	Yes	Yes	Yes
Observations	995	995	991	927
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.395	0.419	0.463	0.492
Number of Municipalities	144	144	144	133

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 16

Effect over poverty rates, excluding years 2011 & 2013

	(1)	(2)	(3)	(4)
Commodity Shock	-0.155**	-0.140**	-0.101*	-0.108*
	(0.066)	(0.068)	(0.054)	(0.056)
Trends (Metal-mining)	-	-	-0.001	-0.001
			(0.002)	(0.002)
Trends (Non Metal-mining)	-	-	0.003	0.003
			(0.002)	(0.002)
Poverty98⋆Pindex	-	-	-0.240***	-0.237***
			(0.022)	(0.023)
Controls	No	Yes	Yes	Yes
Observations	968	968	959	911
Year Fixed-Effects	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes
R-squared	0.436	0.462	0.531	0.532
Number of Municipalities	196	196	195	183

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 17

Effect over poverty rates and Transmission Mechanisms for repeated counties [1998 - 2013]

	Poverty	Total Employment	Metal Employment	Non-Metal Employment	Skilled Employment	Unskilled Employment	Skilled Metal Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Commodity Shock	-0.124***	0.055**	0.083***	-0.028	0.016	0.039*	0.014
	(0.045)	(0.022)	(0.020)	(0.024)	(0.016)	(0.023)	(0.011)
Trends (Metal-mining)	0.002	0.006***	0.001***	0.005***	0.000	0.006***	0.000***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Trends (Non Metal-mining)	0.005***	0.007***	0.000*	0.007***	0.001*	0.006***	0.000**
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Poverty98*Pindex	-0.212***	-	-	-	-	-	-
	(0.018)	-	-	-	-	-	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,264	1,264	1,264	1,264	1,264	1,264	1,264
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.458	0.354	0.322	0.273	0.313	0.376	0.124
Number of Municipalities	182	182	182	182	182	182	182

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 18

Effect over poverty rates and Transmission Mechanisms for repeated counties [1998 - 2013]

	Unskilled Metal Employment	Total Wages (Mean)	Total Wages (Median)	Skilled Workers Wages (Mean)	Skilled Workers Wages (Median)	Unskilled Workers Wages (Mean)	Unskilled Workers Wages (Median)
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Commodity Shock	0.067***	0.471***	0.468***	0.199	0.209	0.471***	0.426***
	(0.024)	(0.160)	(0.086)	(0.238)	(0.169)	(0.070)	(0.088)
Trends (Metal-mining)	0.001	0.058***	0.115***	0.103***	0.132***	0.084***	0.113***
	(0.001)	(0.005)	(0.003)	(0.008)	(0.008)	(0.004)	(0.003)
Trends (Non Metal-mining)	-0.001	0.048***	0.112***	0.103***	0.135***	0.072***	0.110***
	(0.001)	(0.004)	(0.003)	(0.008)	(0.006)	(0.004)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,264	1,264	1,264	1,263	1,263	1,264	1,264
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.292	0.625	0.935	0.591	0.718	0.845	0.945
Number of Municipalities	182	182	182	182	182	182	182

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 19

Effect of Other Commodities [1998 - 2013]

	Poverty	Poverty	Total Employment	Unskilled Metal Employment	Total Wages (Median)	Unskilled Workers Wages (Median)
	(1)	(2)	(3)	(4)	(5)	(6)
Commodity Shock	-0.174***	-0.112**	0.054**	0.078***	0.559***	0.512***
	(0.066)	(0.045)	(0.022)	(0.023)	(0.088)	(0.083)
Other Commodities Shock	-0.077*	0.046	-0.024	0.043***	0.431***	0.423***
	(0.043)	(0.038)	(0.024)	(0.014)	(0.061)	(0.053)
Trends (Metal-mining)	-	0.002	0.005***	-0.000	0.102***	0.097***
		(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Trends (Non Metal-mining)	-	0.005***	0.006***	-0.002*	0.100***	0.094***
		(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Poverty98*Pindex	-	-0.219***	0.017	0.013	0.114***	0.179***
		(0.017)	(0.011)	(0.010)	(0.033)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1356	1356	1356	1356	1356	1356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.372	0.434	0.325	0.288	0.933	0.940
Number of Municipalities	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 20

Commodity Shock on Relative Poverty Rates [1998-2013]

	(1)	(2)	(3)
Commodity Shock	-0.275***	-0.268***	-0.120***
	(0.055)	(0.063)	(0.040)
Trends (Metal-mining)	0.004*	0.008***	-0.010***
	(0.002)	(0.002)	(0.002)
Trends (Non Metal-mining)	0.005**	0.009***	-0.009***
	(0.002)	(0.003)	(0.002)
Poverty98⋆Pindex	-0.095***	-0.081***	-0.044***
	(0.019)	(0.023)	(0.015)
Controls	Yes	Yes	Yes
Observations	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes
R-squared	0.288	0.291	0.293
Number of Municipalities	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Columns 1, 2 and 3 are the estimation when relative poverty is defined as households income below to the average of the county, below to the median of the county, and below to the 50% of the median respectively.

Table 21

Poverty rates and different Exposure Levels

	(1)	(2)
Commodity Shock	-0.138**	-0.136***
	(0.057)	(0.047)
Trends (Metal-mining)	-0.004*	0.002
	(0.002)	(0.002)
Trends (Non Metal-mining)	-0.001	0.005***
	(0.002)	(0.002)
Poverty98⋆Pindex	-0.120***	-0.212***
	(0.020)	(0.017)
Controls	Yes	Yes
Observations	1,160	1,356
Year Fixed-Effects	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes
R-squared	0.360	0.433
Number of Municipalities	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Column 1 is for metal-mining employment share in 2000, and column 2 is for the average of metal-mining employment between 1998 and 2000

Table 22

Poverty rates and Migration

	(1)	(2)	(3)
Commodity Shock	-0.118**	-0.118**	-0.177***
	(0.045)	(0.046)	(0.059)
Trends (Metal-mining)	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)
Trends (Non Metal-mining)	0.005***	0.004**	0.004
	(0.002)	(0.002)	(0.003)
Poverty98⋆Pindex	-0.208***	-0.202***	-0.196***
	(0.019)	(0.020)	(0.023)
Controls	Yes	Yes	Yes
Observations	1,283	1,188	959
Year Fixed-Effects	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes
R-squared	0.443	0.454	0.468
Number of Municipalities	185	171	138

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Column 1 is excluding counties with average migration rate higher than percentile 95 of the distribution, column 2 is excluding those higher that percentile 90, and column 3 is for a threshold in percentile 75. The average migration rate is weighted by population, and calculated only for year 2006-2013 where migration data is available.

Table 23

Effect on Total Employment Share for Industries* [1998 - 2013]

	Agriculture (1)	Mining (2)	Manufacturing (3)	Electricity (4)	Construction (5)	Commerce (6)	Transport (7)	Finances (8)	Services (9)
Commodity Shock	-0.002	0.135***	0.014	-0.023**	-0.094***	0.022	-0.022	-0.028**	-0.013
	(0.046)	(0.050)	(0.019)	(0.010)	(0.030)	(0.028)	(0.023)	(0.012)	(0.028)
Trends (Metal-mining)	-0.004*	0.003***	-0.004***	0.000	0.001	0.006***	-0.001	0.002**	-0.004**
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Trends (Non Metal-mining)	-0.004	0.001	-0.004***	-0.001**	0.002*	0.007***	0.000	0.001	-0.003*
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Poverty98*Pindex	-0.080***	0.011	0.050***	0.007**	0.017	-0.010	0.004	-0.004	0.017
	(0.020)	(0.015)	(0.015)	(0.003)	(0.012)	(0.016)	(0.007)	(0.008)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,335	1,064	1,348	1,045	1,354	1,356	1,349	1,290	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.280	0.220	0.138	0.061	0.048	0.250	0.020	0.113	0.046
Number of Municipalities	196	194	196	194	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

(*) Industries are divided according to CIIU classification

Table 24

Effect on Total Wages (Median) for Industries* [1998 - 2013]

	Agriculture (1)	Mining (2)	Manufacturing (3)	Electricity (4)	Construction (5)	Commerce (6)	Transport (7)	Finances (8)	Services (9)
Commodity Shock	0.488**	0.186	0.470**	0.533	0.693***	0.418***	0.594***	0.867***	0.182
	(0.221)	(0.221)	(0.220)	(0.441)	(0.189)	(0.160)	(0.206)	(0.269)	(0.138)
Trends (Metal-mining)	0.085***	0.077***	0.084***	0.055***	0.082***	0.077***	0.090***	0.093***	0.119***
	(0.019)	(0.018)	(0.008)	(0.021)	(0.008)	(0.005)	(0.008)	(0.015)	(0.007)
Trends (Non Metal-mining)	0.093***	0.125***	0.086***	0.066***	0.085***	0.076***	0.081***	0.090***	0.117***
	(0.015)	(0.018)	(0.007)	(0.017)	(0.007)	(0.004)	(0.008)	(0.014)	(0.006)
Poverty98*Pindex	0.275*	0.453**	0.224***	-0.070	0.213**	0.209***	0.229***	-0.218	0.078
	(0.150)	(0.221)	(0.080)	(0.207)	(0.084)	(0.055)	(0.081)	(0.138)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,329	1,039	1,347	1,011	1,352	1,356	1,345	1,276	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.550	0.432	0.598	0.265	0.701	0.744	0.603	0.346	0.824
Number of Municipalities	196	194	196	194	196	196	196	195	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

(*) Industries are divided according to CIIU classification

Table 25

Effect on Female Employment Share [1998 - 2013]

	Total	Total	Agriculture	Mining	Manufacturing	Electricity	Construction	Commerce	Transport	Finances	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Commodity Shock	-0.007	0.011	-0.035***	0.036***	0.007	-0.002	-0.001	0.015	-0.005	-0.021***	0.018
	(0.024)	(0.025)	(0.013)	(0.012)	(0.007)	(0.002)	(0.003)	(0.015)	(0.006)	(0.008)	(0.022)
Other Commodities Shock		0.074**	0.017	-0.000	0.048***	0.004	0.002	-0.018	-0.008	-0.027***	0.058**
		(0.030)	(0.021)	(0.003)	(0.009)	(0.003)	(0.004)	(0.019)	(0.005)	(0.008)	(0.024)
Trends (Metal-mining)	0.003**	0.003**	-0.001	0.000*	-0.001***	0.000**	0.000	0.004***	0.000	0.001***	-0.002
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Trends (Non Metal-mining)	0.003***	0.003***	-0.000	0.000**	-0.002***	0.000*	0.000	0.004***	0.001***	0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Poverty98*Pindex	0.066***	0.054***	0.018**	-0.001	0.010**	-0.000	0.000	0.000	-0.002	0.003	0.026*
	(0.014)	(0.015)	(0.008)	(0.001)	(0.005)	(0.001)	(0.002)	(0.010)	(0.003)	(0.004)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,356	1,356	1,356	1,356	1,356	1,356	1,356	1,356	1,356	1,356	1,356
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.328	0.334	0.079	0.151	0.092	0.037	0.023	0.201	0.033	0.094	0.077
Number of Municipalities	196	196	196	196	196	196	196	196	196	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Industries are divided according to CIIU classification

Table 26

Commodity Shock and Dutch Disease [1998-2013]

	(1)	(2)
Commodity Shock	-0.161**	-0.123***
	(0.066)	(0.044)
Dutch Disease	0.023	0.014
	(0.043)	(0.034)
Trends (Metal-mining)		0.001
		(0.002)
Trends (Non Metal-mining)		0.005***
		(0.002)
Poverty98⋆Pindex		-0.210***
		(0.017)
Controls	Yes	Yes
Observations	1,348	1,348
Year Fixed-Effects	Yes	Yes
Muncipality Fixed-Effects	Yes	Yes
R-squared	0.381	0.447
Number of Municipalities	196	196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The Dutch Disease variable is the interaction between the metal's price index and the share of employment in metal-mining and manufacturing industries in 1998, in counties intensives in both industries.

Table 27

Table A1. Descriptive Statistics of Observations in CASEN's - [1998-2013]

	1998	**2000**	**2003**	**2006**	**2009**	**2011**	**2013**	**Average**
National Poverty Rate*	20.1%	20.5%	18.6%	15.1%	14.9%	14.4%	13.7%	16.8%
Surveyed Households	48,107	65,036	68,153	73,720	71,460	59,084	66,725	64,612
Surveyed Individuals	188,360	252,748	257,077	268,873	246,924	200,302	218,491	233,254
Implied National Population*	13,143,833	14,361,014	15,340,042	16,115,197	16,584,521	16,902,542	17,218,400	15,666,507
Municipalities	196	285	302	335	334	324	324	300

Note: (*) indicates that the variable is computed with municipal expansion factors provided in CASEN

Table A2. Source an Definition of each variable

Variable	Source	Definition
Cooper Price	COCHILCO	Dollars per pound of refined cooper (U$/lb) - London Metal Exchange: Copper Grade A Settlement.
Molybdenum Price	COCHILCO	Dollars per pound of molybdenum (U$/lb) - US Dealers.
Gold Price	COCHILCO	Dollars per ounce of gold (U$/oz) - HANDY & HARMAN.
Silver Price	COCHILCO	Dollars per ounce of silver (U$/oz) - HANDY & HARMAN.
Iron Ore Price	FMI - Macroeconomic Statistics	Dollars per Metric Tons of iron ore (U$/MT).
Cooper Production	COCHILCO	Thousands of Metric Tons (MT).
Molybdenum Production	COCHILCO	Metric Tons (MT) of Fine Content.
Gold Production	COCHILCO	Kilograms (Kg) of Fine Content.
Silver Production	COCHILCO	Kilograms (Kg) of Fine Content.
Iron Ore Production	COCHILCO	Thousands of Metric Tons (MT).
Price Index weighted by production	COCHILCO	Index of metal prices, weighted by production of each metal over total production of five metals.
Price Index weighted by value of production	COCHILCO	Index of metal prices, weighted by value of production over total value of production of five metals.
Metal Mining Share	CASEN	Ratio of workers employed metal mining (ISIC Rev.3 1310 and 1320) over total municipal employment.
Municipal Poverty Rate	CASEN	Ratio of poor people, over total municipal popullation. An individual is defined as "poor" if their income (or income per-capita of the household) doesn't covers the cost of a Basic Food Basket, and a Basic Non-Food Basket. So, the poverty thresholds is the total value of both baskets.
Municipality Size	CASEN	Number of people living in each municipality.
Average Schooling	CASEN	Average years of schooling for older than 15 years.
Avg. Number of persons in households	CASEN	Average number of persons per household, for each monucipality.
Ethnic Share	CASEN	Ratio of people who belong to an ethnic, over total municipal popullation.
Urban Share	CASEN	Ratio of people living in urban area, over total municipal popullation.
Skilled Workers	CASEN	Workers who at most ended high school.
Unskilled Workers	CASEN	Workers with more education than high school.
Average Wages - skilled workers	CASEN	Average wages (income from main occupation) of skilled workers, for each municipality.
Average Wages - unskilled workers	CASEN	Average wages (income from main occupation) of unkilled workers, for each municipality.

Table A3. Percentage* of Skilled and Unskilled workers over each Economic Sector - (1998-2013)

	Mining		Agriculture		Trade		Construction		Electricity	
Year	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled
1998	26.3%	73.7%	17.4%	82.6%	15.9%	84.1%	16.5%	83.5%	26.4%	73.6%
2000	32.5%	67.5%	5.6%	94.4%	17.1%	82.9%	13.4%	86.6%	46.2%	53.8%
2003	34.5%	65.5%	6.1%	93.9%	20.0%	80.0%	15.3%	84.7%	36.2%	63.8%
2006	20.0%	80.0%	3.6%	96.4%	10.7%	89.3%	9.2%	90.8%	25.2%	74.8%
2009	27.9%	72.1%	6.1%	93.9%	20.5%	79.5%	14.6%	85.4%	33.3%	66.7%
2011	23.0%	77.0%	5.1%	94.9%	11.5%	88.5%	9.9%	90.1%	29.1%	70.9%
2013	30.2%	69.8%	5.4%	94.6%	19.3%	80.7%	14.8%	85.2%	25.1%	74.9%

	Financial		Manufacturing		Services		Transportation		Metal-Mining	
Year	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled	% Skilled	% Unskilled
1998	36.8%	63.2%	16.2%	83.8%	31.5%	68.5%	16.2%	83.8%	27.6%	72.4%
2000	47.2%	52.8%	19.7%	80.3%	34.0%	66.0%	18.0%	82.0%	34.7%	65.3%
2003	53.9%	46.1%	19.5%	80.5%	36.5%	63.5%	21.9%	78.1%	37.3%	62.7%
2006	36.4%	63.6%	12.4%	87.6%	27.9%	72.1%	14.3%	85.7%	21.4%	78.6%
2009	49.7%	50.3%	20.2%	79.8%	39.4%	60.6%	22.6%	77.4%	29.3%	70.7%
2011	38.3%	61.7%	13.1%	86.9%	34.0%	66.0%	14.2%	85.8%	23.8%	76.2%
2013	52.3%	47.7%	17.3%	82.7%	44.3%	55.7%	21.9%	78.1%	30.0%	70.0%

Source: Own elaboration using CASEN data [1998-2013]

(*) Is the percentage over total employment of the economic sector (Skilled + Unskilled).

Table A4. Evolution of different Average Municipal Consumer Price Index (MCPI), Index for Rental Cost, Rental Cost, National CPI, and Wages [2000-2013]

Year	National CPI*	Rental Cost Index*	Rental Cost Metal-mining counties ($)	Rental Cost Non metal-mining counties ($)	MCPI Metal-mining counties [1]*	MCPI Non metal-mining counties [1]*	MCPI Metal-mining counties [2]*	MCPI Non metal-mining counties [2]*	Wages of Metal-mining counties ($)	Wages of Non metal-mining counties ($)
2000	96.0	97.3	53629.1	62445.0	96.0	96.0	96.2	95.8	248547.9	262718.8
2003	100.0	100.0	60142.2	67700.0	100.0	100.0	100.0	100.0	273068.8	285985.5
2006	107.6	110.7	62759.9	70843.0	107.9	107.7	109.9	108.1	306241.1	303240.5
2009	116.9	128.5	79758.7	78568.6	118.0	117.1	127.9	118.4	362866.5	355063.7
2011	123.0	163.4	98271.0	99821.9	125.1	124.2	144.6	135.5	350379.3	332084.0
2013	127.5	185.5	118961.9	111950.1	131.2	129.3	165.0	145.5	350377.3	323498.0
Change 2000-2013	32.8	90.7	121.8	79.3	36.6	34.7	71.5	51.9	41.0	23.1

* 2003=100

Note: we create the National CPI using weighting factors of the 2008's based basket. This, to capture the changes in the consumers price index due to rental costs changes and not of the weighting factors.

[1] mean that MCPI is created using the index for the rental cost of apartments and houses, and the weighting factor for these index is 3.9% approximately.

[2] is the same idea of [1], but now assuming that all non-tradable goods change in the same way than the rental cost of apartments and houses. This means that the weighting factor rises to almost 40%.