Commodity Price Booms and its Impact on Wages

Hriday Karnani*
Universidad de Chile

June 21, 2022

Abstract

This paper studies the impact of a commodity price boom that occurred during the beginning of the 2000s on real wages of Chilean workers. We use a household survey data between 2000 and 2009 and a difference-in-difference strategy to examine the effect. With our estimates, we find that the shock generated an increase of about 4.7% in the real wages of workers in the mining sector.

1 Introduction

In the first decade of the 21st century the world experienced a significant increase in commodity prices. The impact of this positive terms of trade shock can be studied in several dimensions and variables. This shock should have a higher impact on countries that have large endowments of natural resources, but even among these countries, the impact is probably heterogeneous due to institutional and labor market factors, among others. Chile is one of the main producers and exporters of copper, mineral that experienced a sharp increase in its price between 2003 and ~2008 (Figure 1).

The impact of such a shock over some dimensions of welfare is not obvious. For example, some of the existing literature analyzes the "Dutch Disease" (Krugman, 1987), which suggests that shocks on terms of trade should have a negative effect over the economic activity in the medium term. There also exists literature that challenges this view and concludes that such a shock has a positive impact over economic activity and some variables that measure economic welfare (Álvarez et al., 2021; Aragón and Rud, 2013).

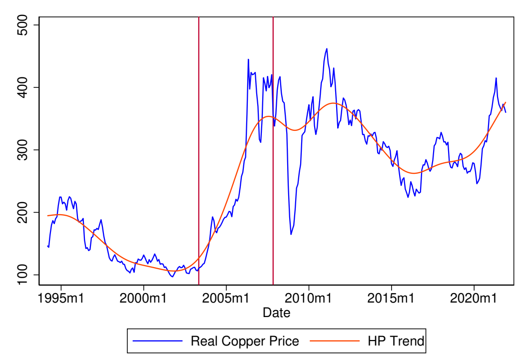

Figure 1: Real Copper Price

The event resulted in higher profits for the mining companies, which can be seen in the large increase in revenues that the main state owned mine, Codelco, had during the period (Cochilco, 2013). But, according to micro theory, it could also generate a spillover effect on the wages of mining workers and even over other sector wages. The objective of

*Email: hkarnani@fen.uchile.cl.

this paper is to study the impact of this commodity price boom over real wages of Chilean workers and to bring new information and insights to understand whether this spillover effect happened in practice or not, while also trying to understand if higher profits for companies are transferred, and in what extent, to their workers. Our contribution is centered on giving a quantitative estimation of the impact of the shock with a difference-in-difference approach, aiming to gain a causal effect and complementing the existing literature on the impact of natural resources boom, presenting evidence of their effect over an economy as the Chilean.

We propose and estimate three different models to analyze quantitatively the impact of this shock. The first one is based on a novel PSM-DiD approach, the second analyses the impact of the shock over wage premia and analysis the potential impact over wage distribution and inequality, while the third model aims to account for spillovers in different sectors of the economy. With these three different approaches, we find that the commodity price boom increased real wages of mining workers by approximately 4.7%.

The paper is organized as follows. Section 2 motivates the theory behind our investigation, reviews literature and explains the importance of copper price in an economy like the Chilean. Section 3 describes the data and our quantitative approach to this problem. Section 4 shows the results from our three specifications. Section 5 performs a battery of robustness checks and section 6 concludes.

2 Motivating Framework

Historically, Chile has been a mining country, from its beginnings as a nitrate exporter in the nineteenth century, to when it began to encourage investment to develop the large-scale copper industry in the twentieth century. Despite the constant criticism over the country's overdependence on copper and the efforts trying to change the productive matrix, 80% of Chile's export earnings continue to come from a couple of products: copper, fruit, fish and wood (Pellandra, 2015).

The impact of this commodity price boom on export earnings has been analyzed and Chinese growing demand has been determined as the key factor that stimulated world prices of copper (Yu, 2011). The growing Chinese demand is in line with its incorporation to the WTO, increasing its integration with the world economy and trade. China, as a producer of energy intensive industries, increased its demand of metals. China's copper consumption increased from 20% of the world total in 2003 to 40% in 2011 (Cochilco, 2013).

Thus, it seems plausible to conclude that the origin of the shock was external and exogenous for Chile, rather than because of an increase in marginal production costs. This is a key feature over our identification strategy that will be presented on the next section.

Micro theory suggests that there are two key channels in which the price boom can affect the economy: a wealth channel, through which higher commodity prices increase domestic demand, and a cost channel, through which they induce wage increases (Benguria et al, 2018). This also gets catalyzed by the fact that the copper price boom raises demand for labor in the mining sector leading to an increase in wages.

However, there are at least two clear reasons why the latter might not be true. First, if we face imperfect competition, copper firms may be extracting some rent so an increase in price just increases this rent and the worker's wages remain the same. If this is the case, employers' greater bargaining power may explain why price increases are not passed on to workers' wages, but if the firm faces imperfect competition then we would also expect stronger worker unions, fact that challenges the first theory. Second, the price increase may benefit employment instead of wages. Although labor market frictions make this hypothesis not very feasible.

Concerning macro theory, we can also think of Stolper-Samuelson (1941) theorem, which states that an increase in prices will generate an even larger increase in the cost of factors that the firm is intensive in. This way, if the copper mining sector is labor intensive we would expect a sharp increase (proportionally larger than the initial price increase) in wages and a decrease in the cost of capital when facing a copper price shock. The opposite happens if the sector is capital intensive. With respect to this last point, the Chilean copper mining sector requires both labor and capital in a very large scale, however, we would think that the industry is capital intensive because it is known that mining worker unions are very strong in Chile (specially in the state-owned enterprise Codelco), and this bargaining power can come from the fact that changes in wages do not affect the firm's cost structure in a very large scale (if the firm is capital intensive).

This paper will try to answer these questions and disentangle copper price boom actual effects in mining workers' wages.

If we compare this theoretical framework with empirical evidence in what has been studied, we notice that González (2021) shows that in an economy with variable factor utilization, there is a strong relationship between copper price shocks and aggregate productivity, as it is observed in Chilean data. This way, we can support the theory that higher prices induce higher productivity and that could imply higher wages. However, this increase in wages can be heterogeneous as Pellandra (2015) shows in her study, where a price shock affects more those regions with a higher exposure to mining companies by increasing unskilled workers wages relatively to other regions. Also, she shows that there is employment reallocation from unaffected sectors to the sector that benefited from the price increase, but much less evidence of mobility across regions.

Similar to our study, Aragón and Rud (2013) examine the local economic impact of the expansion of a large gold mine in Peru, finding positive evidence of mine's demand for local inputs and real income with a difference-in-difference approach, exploiting the geographical distance to the location of the gold mine. Finally, as a summary of the effects of a commodity boom, Álvarez et al. (2021) shows that a positive terms of trade shock reduces poverty rates and it also has significant effects on wages and employment, specially in mining workers and unskilled labor.

In this context, our paper will address the effect of a copper price boom in wages directly in order to extract new insights and to contribute to the discussion over the impact of commodity price booms over local economies.

3 Data and Methodology

Our data is provided mainly by the Chilean National Socioeconomic Characterization (CASEN) Survey. This is a repeated cross-section survey that is applied every two or three years on a subset of Chilean households and is the main source for socioeconomic statistics in the country. We obtain the industry in which each worker surveyed works, income data, years of education and other observable characteristics of individuals from this source.

In this project, we use four CASEN surveys applied during 2000 and 2009. Additionally, we rely on Cochilco to obtain data on copper prices, the Central Bank of Chile for consumer price index (in order to compare real wages), and the OECD Input-Output Tables to analyze the connection as suppliers and sellers that each sector of the economy has with the mining sector in Chile. Summary statistics can be observed in Table 4 (Appendix).

As it was detailed in the past section, commodity price booms are an exogenous event, in this case originated by the increase in demand of emerging markets (mainly China). Considering this and the hypothesis that the event should impact mostly to the mining sector, we will use a difference-in-difference (DiD) approach comparing the wages of workers in the mining sector with those in non-mining sectors before and after the boom. With this approach we aim to face the challenge of a biased estimation, while considering the pre-existing differences between the two groups. In order to use this strategy, we need to have a valid counterfactual for out treated group (mining sector workers). To address this concern, we follow a Propensity Score Matching (PSM) strategy to match individuals from the treated group to the control group across their observable characteristics.

Since CASEN is not a panel database but it is a repeated cross section, we have to find a strategy to observe a similar control and treatment group over time. We face a scenario where we observe data at a baseline period (pre-shock) and midline period (post-shock). The two methods often used to obtain an unbiased estimate of the impact under these conditions are PSM and DiD. Thus, we follow a novel PSM-DID approach, as in Binci et al. (2018) and Heckman et al. (1997).

With PSM we match individuals on their probability of being treated, thereby creating a comparable counterfactual for each treated observation. DID is an analytical approach where imbalances between the two groups are differenced over the waves of data to isolate the attributable impact of the commodity price boom shock. The combination of these two approaches tries to offset their individual weaknesses. As it is demonstrated in Heckman et al. (1997), the PSM-DID estimator removes selection on observables (with PSM) and on unobservables (with DiD).

PSM consists in a two-stage analytical approach. Based on a set of observable characteristics for each individual, we compute the probability of being treated of each observation (including the treated group) with a logit estimator, as follows:

$$Pr(T=1|X_i) = \frac{e^{\alpha+\beta X_i}}{1+e^{\alpha+\beta X_i}}$$

Where $Pr(T = 1|X_i)$ is the probability of being treated conditional on a vector of characteristics, X_i, for each individual i. $\alpha + \beta X_i$ is the linear model that estimates the probability of being treated, which is estimated with maximum likelihood. The vector X of observable characteristics contains years of education, region of residence, gender, age and years of experience.

Based on the previous probabilities, we match each treated observation with a K Nearest Neighbor approach, without replacing. This means that each treated observation i is matched with the control observation j that has the nearest distance probability to i of being treated.

We implement three matching processes: (i) Treated-control pre-treatment: For each individual mining worker (treated group) on the pre-treatment period $t-1$ we search for statistically similar control individuals (non-mining worker) in the same period. (ii) Treated-treated pre and post treatment: For each individual mining worker (treated group) in the pre-treatment period, we find a statistically similar mining worker (treated group) in the post-treatment period. (iii) Treated-control post-treatment: For each individual mining worker matched in (ii) from the post-treatment period, we search for statistically similar control individuals (non-mining worker) in the same period.

A good matching process implies that the treated and control groups are similar in their observable characteristics, and therefore they will not be statistically different from each other. To account for this important characteristic, our Summary Statistics (Table 4) compares the treated and control group on their observable characteristics. Note that we did not match over income, so obviously this variable is going to differ across groups, which is later cleaned with the DiD estimation.

With the PSM approach, we create a pseudo panel of treatment and control observations. Since this matching process does not counter for unobserved time-invariant heterogeneity, we combine the previous matching processes with a DiD strategy in the second step.

We specify the year 2003 as the one in which the event started and 2008 as $t+1$ where the price boom ended. This time window can be seen noticing that in Figure 1 the price boom started somewhere in 2003 and ended by 2008. We support this time period formally with a structural break analysis, which concludes that on 2003 there was a structural break on the price series, which changed its direction by 2008.

The latter analysis is useful to define the years for our empirical approach. Considering that (i) the price boom was continuous and did not occur during one single year, (ii) the fact that on its beginning the shock might have been seen as transitory, which implies that salaries would take even more time to adjust, (iii) the existence of sticky wages and (iv) the frequency of our data, for our empirical analysis we define 2003 as the year pre-treatment, and 2006 as the year of the shock, extending it until 2009. Thus, the model in which we base our empirical approach to find the impact of a commodity price boom over wages is:

$$ln(w_{i,t}) = \alpha + \beta S_t + \delta T_i + \gamma T_i S_t + \varphi X_{i,t} + \epsilon_{i,t} \tag{1}$$

Where $w_{i,t}$ is the real wage on individual i on period t, S_t is a dummy indicating if the observation is measured after the shock, T_i is a dummy indicating if individual i is a mining sector worker (treated) and X_i is a set of variables of control which starts by including mincerian variables: years of education, years of experience, (years of experience)^2, gender and a dummy indicating if the individual i has a level of education higher than High School, which is a proxy for skilled workers.

Our parameter of interest is γ, since it captures the impact that the shock had on mining workers wages.

The utility of using a DiD estimator is that, assuming parallel trends (analyzed in Figure 2) and fixed non-observables, it has the ability of eliminating the differences between groups in non-observables and observables (which were partially already eliminated with PSM), allowing us to obtain an unbiased estimator.

A concern that might still be active from our empirical approach is the possibility of spillover in our control group. We address this concern with a robustness check, where we change our control group to an economic sector that is mostly unrelated to the mining sector: the agricultural sector. A detailed description of this approach can be seen on our robustness checks section.

The base assumption of our DiD approach is parallel trends, we check for them visually on the following figure:

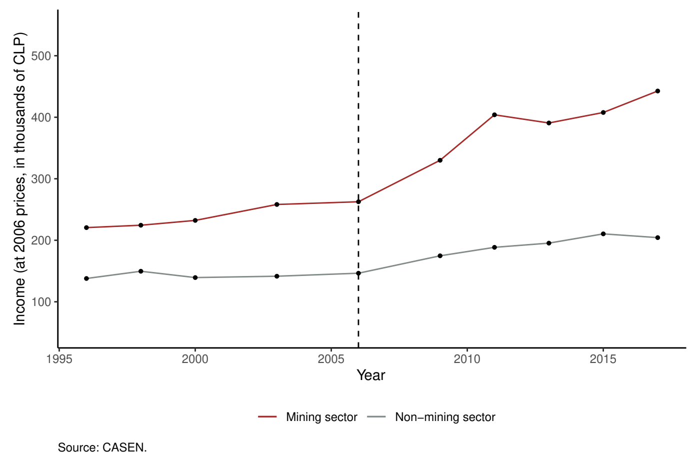

Figure 2: Income from the main occupation.

With this figure we can observe that parallel trends assumption seems plausible.

4 Results

We provide three different approaches, based on our model explained in Section 3, to estimate the impact of this commodity price boom over wages of Chilean workers. Our first approach is the basic PSM-DID model proposed on Equation (1), the second model follows existing literature and estimates the impact of the shock over the wage premia of mining workers. Finally, our third approach aims to consider the possibility of the shock having an impact over more sectors using the connections that each Chilean economic sector has with the mining sector, measured with OECD Input-Output tables.

4.1 Main PSM-DID Estimation

In this section we present the main results of the model proposed on Section 3. Table 1 estimates three models, the first column shows a simple difference-in-difference estimation without any controls, while the second column shows the model presented on Equation 1 considering Mincerian variables as controls. The third column includes controls of gender and skilled workers.

Table 1: PSM-DID estimation

	ln(Wage)	ln(Wage)	ln(Wage)
Treatment*Shock	0.047**	0.047**	0.048***
	(0.023)	(0.019)	(0.018)
Treatment	0.290***	0.298***	0.299***
	(0.019)	(0.015)	(0.015)
Shock	0.066***	0.067***	0.080***
	(0.008)	(0.007)	(0.007)
Education		0.107***	0.085***
		(0.001)	(0.001)
Experience		0.031***	0.032***
		(0.001)	(0.001)
Experience^2		−0.000***	−0.000***
		(0.000)	(0.000)
Gender			−0.306***
			(0.016)
High School			0.276***
			(0.011)
Intercept	12.218***	10.575***	11.081***
	(0.007)	(0.017)	(0.024)
Controls	No	Yes	Yes
R^2	0.022	0.258	0.276
Adj. R^2	0.022	0.257	0.276
Num. obs.	42372	42372	42372

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Notes: Robust standard errors in parenthesis.

Our estimation suggests that the fact of being a mining worker during the shock generated an extra increase of approximately 4.7-4.8% in real wages from the main income, with p-values lower than the standard acceptable values. We also find that the shock had a positive impact over the whole economy (including non-mining workers) between 6.6-8%. As observed in Figure 2, we observe that mining workers earn a higher wage that non-mining workers, which is also validated by our model, that suggests that the fact of being part of the treatment group implies a 30% higher real wage. Our control variables behave as expected, with positive returns for years of education and experience. We also observe a gender gap (with men earning more than women, since Gender is a dummy equal to 1 if an individual is a women) and positive returns for skilled workers.

Further, we highlight the robustness of the estimation of our main variable of interest (Treatment*Shock) to different specifications and control variables. For each of the three estimations, the coefficient is stable between 4.7-4.8%. As expected, when we include control variables to our DiD estimation we observe that the standard error of our coefficient diminishes.

Comparing this result with related literature, the results shown on Table 1 are in line with it. Álvarez et al. (2021) find that a commodity price boom reduced poverty by more than 2% points in municipalities relatively exposed to the commodity boom and Pellandra (2015), shows that a region exposed to a 10% increase in average prices (or a 10 dollars per worker exogenous increase in exports) experienced a 2.4% increase in average unskilled workers' wages relatively to other regions.

4.2 Wage Premia Estimation

An interesting way of analyzing the impact of the commodity price boom over wages is checking if the wage premia increased for mining workers due to this shock. Following Pellandra (2015), we define and estimate the wage premia as the difference between the effective and predicted income of an individual. Using a Mincerian regression and adding gender as an extra control, we estimate the predicted wage that each individual should have, the residuals of the regression are the wage premia. The estimation is as follows, in the first stage we estimate a simple OLS regression with real wages as a dependent variable and a set of individual characteristics:

$$ln(w_{i,t}) = \alpha + \beta X_{i,t} + \mu_{i,t}$$

The second stage consists on using estimated

$\hat{\mu}_{i,t}$ as a dependent variable and estimate a simple difference-in-difference, without any controls.

$$\hat{\mu}_{i,t} = \alpha + \beta S_t + \delta T_i + \gamma T_i S_t + \epsilon_{i,t}$$

Intuitively, we would expect mining workers to see an increase in their real wages. But because their observable characteristics have not changed relative to non-mining workers, their predicted wages should remain the same. Then, we would expect that the commodity price boom should increase the wage premia for mining workers.

Table 2: Mincer Wage Premia Estimation

	Mincer Wage Premia
Treatment*Shock	0.045^{**}
	(0.020)
Treatment	0.299^{***}
	(0.017)
Shock	0.071^{***}
	(0.007)
Intercept	-0.084^{***}
	(0.006)
R^2	0.031
Adj. R^2	0.031
Num. obs.	42372

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Robust standard errors in parenthesis.

These results suggest that wage premia increases for mining workers after the shock, just as what we mentioned in the previous paragraph. With a different point of view, this makes sense because mining workers have a higher proportion of low qualified labour. A positive commodity price shock makes the worker's skill relatively less valuable and benefits them just because they are mining sector workers via an increase in their wage premia. The magnitude of the effect is 4.5%, in line with the estimations of our main model in the previous section.

With this estimation we can also analyze the impact of the shock over the returns that the labour market offers for individuals. An example might make this point in a clearer way: Suppose that an individual with medium level skills that works in the mining sector as a manual worker will remain with a similar level of "medium quality" observable characteristics after the shock, but because of the shock, he will see increased his wage to higher levels, comparable, for example, to the wage from a worker with "high quality" observable characteristics. Then, the shock would have reduced the wage gap between those individuals and thus, the skill premia might fall. The skill premia is basically the returns in wage that an individual has due to his observable skill characteristics. Thus, this might also have an impact over the distribution of wages and inequality over the whole economy, but this effect goes further our objective in this paper.

The distribution of wages and inequality analysis relies on the assumption that the wages of other sectors do not change in a high magnitude with the shock (i.e., spillovers are not relevant). Clearly, this does not seem like a credible assumption. In the next subsection we aim to analyze the effect allowing for spillovers.

4.3 Mining Sector Linkages Estimation

The objective of this section is analyzing the impact of the shock over wages while allowing the shock to have an impact over more than one sector. For it, we rely on Input-Output Tables from the OECD, which provides us the connection that each sector of the economy has with each other.

The data consists in an annual matrix for each country with the amount of sales (output) and supplies (input) that each sector performs to the other. The matrix contains 45 sectors, but since CASEN survey only gives 9 options of sectors, we synthesis the 45x45 matrix into one of 9x9. We extract the data for the same years in which we use the CASEN survey.

Since the commodity price boom is mainly over the mining sector, for each year we only consider the input and output connections that the mining sector has with each other sector of the economy. Further, the boom should have a higher impact over those sectors that are suppliers of the mining sector. Then, considering the sector in which each individual works, we assign to each of them a variable that accounts for the connection that the economic sector in which they are involved has with the mining sector.

Now, we change our basic DiD model where we used to define the treatment status only for mining sector workers, to a continuous variable between 0 and 1 that is the shares of total supplies that the sector of individual i provides to the mining sector[1]. Note that each sector can interact with each other. Then, it is clear that the mining sector can interact with itself and that is what we observe in the data, where the shares of supplies that the mining sector provides to the same mining sector accounts for approximately 70%. This is useful for our analysis, since we also know that mining sector workers are those that, at least theoretically, should have a higher return because of the shock.

In brief, with this model we attempt to account for different impacts that the shock might have over different economic sectors.

The model we estimate is the following:

$$ln(w_{i,t}) = \alpha + \beta S_t + \delta IN_{i,t} + \gamma IN_{i,t} S_t + \varphi X_{i,t} + \epsilon_{i,t} \quad (2)$$

The only change with respect to Equation (1) is the treatment variable, which is now defined as $IN_{i,t}$.

We estimate the model in Equation (2) with and without the vector $X_{i,t}$, which are columns 1 and 2 of Table 3. On the column 3 we maintain the original Equation (1) but we add as a control the input shares of each individual, which also attempts to account for the heterogeneity that the shock should have over real wages.

The results show that when accounting for input shares, the impact of the commodity price shock increases to an increase in wages between $14-17\%$, results that are significant at standard acceptable p-values. This might be because we include the spillover that the shock probably had. It can also be noticed that without accounting for the shock, workers from sectors that are bigger suppliers of the mining sector have higher real wages than those with lower connections.

Table 3: Mining Linkages Estimation

	ln(Wage)	ln(Wage)	ln(Wage)
Input Shares*Shock	0.177^{***}	0.141^{***}	
	(0.036)	(0.030)	
Input Shares	0.523^{***}	0.459^{***}	0.332^{***}
	(0.029)	(0.023)	(0.065)
Shock	0.054^{***}	0.059^{***}	0.064^{***}
	(0.009)	(0.007)	(0.007)
Education		0.105^{***}	0.106^{***}
		(0.001)	(0.001)
Experience		0.031^{***}	0.031^{***}
		(0.001)	(0.001)
Experience^2		-0.000^{***}	-0.000^{***}
		(0.000)	(0.000)
Treatment			0.076^{*}
			(0.046)
Treatment*Shock			0.088^{***}
			(0.020)
Intercept	12.194^{***}	10.582^{***}	10.578^{***}
	(0.007)	(0.017)	(0.017)
Controls	No	Yes	Yes
R^2	0.030	0.258	0.258
Adj. R^2	0.030	0.257	0.258
Num. obs.	42372	42372	42372

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Robust standard errors in parenthesis.

In the next section we provide a series of robustness checks.

5 Robustness Checks

Considering our identification strategy, an obvious robustness procedure is to check if the shock took place on the year we mentioned or in another year. In order to consider this possible problem, we

[1] Defining ω_i as the input shares of sector i, $\omega_i = \frac{Shares_{ij}}{\sum_{i=1}^{L} Shares_{ij}}$

perform a placebo test, generating the same regression of our original specification, Equation (1), but changing the year in which the shock occurred. We test this procedure for a shock occurring one period before we specified (2003) in Table 5, which is available on Section 7.2. In the table it is clear that our parameter of interest (γ, Treatment * Shock) does not have significant results and the noise increases in a high magnitude. Thus, if we move the shock to 2003, we do not observe a significant impact on mining workers wages due to the hypothetical shock that could have occured in 2003.

Taking into consideration the concern about our control group and possible spillover effects, we test our empirical approach with agricultural sector workers as our control group. Intuitively, agricultural sector is not so related to the mining sector, thus, we should not expect high spillover effect among both sectors. Empirically, we can support this claim with data from the Input-Output tables used in Section 4.3. In the data, we observe that on average, the agricultural sector only supplies a share of approximately 0.008% of mining sector inputs. Clearly, this is a relatively low value and we could expect for this sector to receive a low spillover from this shock, at least in the short run. Then, it acts like a good control group for our empirical difference-in-difference approach.

We replicate our main PSM-DID regression results in Table 6, where we observe that the coefficient of our variable of interest seems to stay relatively stable compared to what we observed in Table 1.

The two robustness checks procedures were done to support our empirical approach and address valid concerns. Further, we also analyzed different methods and models to study the impact of this commodity price boom in the previous section.

6 Concluding Remarks

Using a propensity score matching and difference-in-difference methodology with survey household level data (CASEN) we estimate the impact of a commodity price boom over real wages of mining sector workers, finding and effect of 4.7% that is quantitatively robust to different specifications. This effect can be interpreted causally because we use data from different years and with our difference-in-difference estimation we clear any non-observable characteristics differences across individuals. One potential problem of our DiD using CASEN data is that this survey is not panel data, so the treated and control groups across time are not the exact same people. To address this concern, we follow a PSM strategy to compare statistically similar individuals across time and thus cleaning any observable characteristics differences.

We extend the previous specification with two additional approaches. First, we analyze the impact of the commodity price boom over wage premia, observing that it increased in a similar magnitude as the one exposed in the previous paragraph. This approach shows implications over the distribution of wages of the whole economy and is an interesting approach for further investigation. We also analyze the impacts of the boom allowing for different sectors of the economy to be exposed to the shock, relative to their connection to the mining sector.

Concerning the validity of our study or potential specification problems, we perform several robustness checks. One of them is to make sure that the control group is effectively isolated from the exogenous copper price shock. To test the robustness of our results taking in account this problem we perform the same estimation changing the control group to agricultural workers. This group intuitively and empirically does not relate to the mining sector, so the wages of the people in it should not be highly exposed to a copper price boom. With this specification, we find an increase of real wage of 3.9%.

Although we effectively find evidence of an increase in wages because of the commodity price boom, we have to keep in mind that the dataset used is just a sample of the population and we cannot extrapolate our results to the whole population or to another countries with different labor market dynamics or different macroeconomic structure and cycles.

The effect found supports the theory of a spillover effect from firm's profits to worker's wages. However, we could extend to further research the labor market mechanisms by which this effect takes place, and if this effect could be more or less depending on the labor market dynamics and structure. Also, this study could be improved using panel data with the exact same individuals across time. Unfortunately, this kind of data is not of easy access. Finally, another extension of our paper could be to explore the relation between the magnitude of the shock and the further wage increase, in line with the theory aspects mentioned previously.

References

- Álvarez, R., García-Marín, Á., Ilabaca, S. (2021). Commodity price shocks and poverty reduction in Chile. Resources Policy, 70, 101177.
- Aragón, Fernando M., and Rud, Juan Pablo (2013). "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine." American Economic Journal: Economic Policy 5(2): 1-25.
- Benguria, F., Saffie, F., & Urzúa, S. (2018). The transmission of commodity price super-cycles (No. w24560). National Bureau of Economic Research.
- Binci, M., Hebbar, M., Jasper, P., Rawle, G. (2018). Matching, differencing on repeat. Propensity score matching and difference-in-differences with repeated cross-sectional data: Methodological guidance and an empirical application in education. Oxford Policy Managment Working Paper.
- Cochilco (2013) Minería en Chile: Impacto en Regiones y Desafíos para su Desarrollo, Comisión Chilena del Cobre, Ministerio de Minería, Santiago, Chile.
- González, G. (2021). Commodity Price Shocks, Factor Utilization, and Productivity Dynamics (Doctoral dissertation, The University of Chicago).
- Heckman, J.J., Ichimura, H., and Todd, P.E. (1997). 'Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme'. Review of Economic Studies 64, 605–654.
- 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 Econonomics. 27 (1–2), 41–55.
- Pellandra, A. (2015). The commodity price boom and regional workers in Chile: a natural resources blessing?. Working Paper Lacerlacea.
- Stolper, W. F., Samuelson, P. A. (1941). Protection and real wages. The Review of Economic Studies, 9(1), 58-73.
- Yu, Yongzheng (2011), "Identifying the Linkage between Major Mining Commodity Circle and China Economic Growth: Its implications for Latin America," IMF Working Paper 11/86, The International Monetary Fund, Washington D.C

7 Appendix

7.1 Summary Statistics

Table 4: Summary Statistics

	Real Median Wage		Avg. Educ. (Years)		Avg. Exp. (Years)		N. Obs.	
Year	Treated	Control	Treated	Control	Treated	Control	Treated	Control
2000	343,156.21	270,216.38	10.04	10.04	23.29	23.21	1554	12432
2003	367,718.88	297,785.43	10.51	10.58	22.79	23.11	1554	12432
2006	379,399.90	287,062.81	10.61	10.70	22.58	22.56	1577	12616
2009	396,982.99	299,262.69	10.70	10.84	21.77	21.96	1577	12616

Note: This table considers observations after matching individuals with Propensity Matching Score. It can be seen that average years of education and experience are similar between both treated and control group. Treated columns refer to mining sector workers, control columns refer to non-mining sector workers.

7.2 Robustness

Table 5: Placebo Difference-in-difference estimation

	ln(Wage)	ln(Wage)	ln(Wage)
Treatment*Shock	0.010	0.027	0.025
	(0.023)	(0.019)	(0.019)
Treatment	0.301^{***}	0.289^{***}	0.292^{***}
	(0.019)	(0.016)	(0.015)
Shock	0.076^{***}	0.015^{**}	0.023^{***}
	(0.008)	(0.007)	(0.007)
Education		0.114^{***}	0.092^{***}
		(0.001)	(0.001)
Experience		0.033^{***}	0.034^{***}
		(0.001)	(0.001)
Experience^2		-0.000^{***}	-0.000^{***}
		(0.000)	(0.000)
Gender			-0.304^{***}
			(0.016)
High School			0.288^{***}
			(0.011)
Intercept	12.142^{***}	10.457^{***}	10.959^{***}
	(0.007)	(0.016)	(0.024)
Controls	No	Yes	Yes
R^2	0.019	0.285	0.303
Adj. R^2	0.019	0.285	0.303
Num. obs.	42165	42165	42165

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Robust standard errors in parenthesis.

Table 6: Agricultural Sector as Control - DiD estimation

	ln(Wage)	ln(Wage)
Treatment*Shock	0.034^{*}	0.039^{**}
	(0.019)	(0.018)
Treatment	0.519^{***}	0.485^{***}
	(0.016)	(0.015)
Shock	0.078^{***}	0.091^{***}
	(0.006)	(0.006)
Education	0.086^{***}	0.065^{***}
	(0.001)	(0.001)
Experience	0.020^{***}	0.019^{***}
	(0.001)	(0.001)
Experience^2	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)
Gender		-0.193^{***}
		(0.010)
High School		0.469^{***}
		(0.016)
Intercept	10.710^{***}	11.105^{***}
	(0.018)	(0.019)
R^2	0.248	0.278
Adj. R^2	0.248	0.278
Num. obs.	42372	42372

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Robust Standard errors in parenthesis.