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RESEARCH ARTICLE

Heterogeneous Impacts of Commodity Price Shocks on Labour Market Outcomes: Evidence and Theory for the Chilean Mining Sector[*†]

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Abstract

Using data for the Chilean mining sector, I provide SVAR evidence in order to answer the research question regarding which are the distributional consequences that commodity price shocks have in labour market outcomes for heterogeneous workers at business cycles frequencies in a Small Open Economy (SOE). I show that an unexpected impulse in commodity prices increases the wage premium between high and low-skilled workers and, at the same time, it decreases the employment level ratio between high skilled and low skilled workers. The latter constitutes a novel finding in the literature of commodity price shocks. In order to rationalize these findings, I build a DSGE-SOE model with asymmetric search and matching (SAM) frictions. The theoretical model, calibrated and estimated with Chilean data, achieves to replicate the empirical labour market dynamics that come from an unexpected increase in the commodity price for the small open economy. Besides, I find that the principal parameters that determine how the commodity shock is going to affect labour market outcomes between high and low-skilled workers are the Nash bargaining power of workers, and the skill intensity in commodity production. The former affects the distribution of wages, and the latter affects the employment level distribution among high and low-skilled workers.

Keywords: DSGE model, Search and Matching, Small Open Economy.
JEL codes: E24, E32, F41, I24, J63.

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1. Introduction

The ups and downs of commodity prices have caught wide attention on macroeconomists in the last two decades. Fernández et al. (2018) have described this phenomenon as a commodity price *roller coaster*. The latter has awaken interest on the effects that commodity price shocks have on domestic economic outcomes. In this regard, there is some consensus that commodity price shocks have positive effects in the domestic economic environment for the exporting countries, as they yield aggregate demand expansions, increasing wages and employment, and real exchange rate appreciations (see Fornero et al. (2014) , Medina and Soto (2016), Bodenstein et al. (2017)). While this view of the effects of commodity price shocks seem, somehow, uncontested, there is still no clear answer to the question regarding how do these kind of shocks affect the different types of agents in the economy, specifically, on different types of workers, considering their wealth or skill (education) level.

To think about the latter, we must understand which mechanisms drive the propagation of commodity price shocks into the economy. There are several ways in which this may happen. The first one is directly into the commodity sector. Better future expectations on commodity prices increase investment projects and the reactivation of current ones on hold which increases the demand for workers within the sector (demand channel), but also they encourage negotiations between the worker unions within the sector and the firms' owners regarding salaries and bonuses (institutional channel). In second place is the indirect effect that commodity price shocks generate outside the commodity sector. Specifically, when commodity prices are higher the sector increases its demand for different kinds of goods and services in sectors such as energy, transport, engineering and consultancy, construction, among others. Workers of those sectors experience higher demand and, thus, higher wages. Third, it is a fact that some commodity sectors are very important for fiscal revenues, such as oil in some Arabic countries or metal mining in Australia or Chile, as they are highly taxed or their production depends directly on public firms. In this regard, fiscal revenues from commodity production can increase employment and wages through, e.g., new public investment projects. Finally, another propagation channel may be the one proposed by Bodenstein et al. (2017), which consists in that commodity price increases yield a real appreciation of the exchange rate which, at the same time, lowers the relative price of domestic goods which increases their demand and, therefore, the labor demand and wages for workers in that sector of the economy. Whichever be the case, it is not obvious how do commodity price shocks affect different workers in the economy, mainly because they are not equal regarding the intensity in the production (commodity or not-commodity), their complementarity with capital, and the frictions they face in the labor market.

In this paper I address the question of which are the distributional consequences on labor market outcomes for heterogeneous workers (differing in their skill level) that arise from commodity price shocks, focusing in the institutional and demand channels of the shock propagation within the Chilean mining sector. I propose a structural model with heterogeneous workers and labor market frictions which allows me to explain a novel stylized fact regarding the effect of copper price shocks on the employment and wage gap between high and low-skilled workers for the Chilean mining sector.

My methodology to give an answer on the issue is, first, by using Chilean time series on the mining sector I provide an SVAR analysis that formalizes the evidence presented above and gives some insights on how do copper price shocks affect labor market outcome gaps between high and low-skilled workers, specifically in the Chilean mining sector. The SVAR analysis shows that, consistent with previous studies, a copper price shock yields positive effects on aggregate demand and job vacancy creation which, at the same time, lowers unemployment levels. Regarding labor market outcome gaps, I find that H-to-L employment level gap (measured by the employment ratio between high and low-skilled workers) decreases on impact and this effect is persistent, lasting more than 10 quarters and, for the wage gap, it increases on impact and afterwards it tends to decrease, but the positive effect is relatively persistent. With this analysis on hand, I propose a DSGE-SOE[1] model in order to rationalize the findings of the SVAR exercise. My model features two main transmission channels of the commodity price shock in the domestic economy: (i) heterogeneous Search and Matching (SAM) frictions and, (ii) skill intensity in commodity production. Heterogeneous SAM frictions allow me to model the labor market taking account on the fact that high and low skilled workers face different labor institutions when searching for a job, and this conditions determine their final outcomes in unemployment and wages (Dolado et al., 2021). Skill intensity in commodity production allows me to account for the fact that commodity production is more intensive in low-skilled workers. This simple model is capable to rationalize quite well the dynamics presented by the SVAR exercise. Finally, I explore how do SAM frictions and skill intensity in commodity production interact in my model, in order to provide a complete answer on how the commodity price shock is transmitted in this framework.

One special point of consideration is that a possible alternative explanation for the empirical effect that I show relies in the classical Stolper-Samuelson result. One extension of the seminal contribution of Stolper and Samuelson (1941) states that, in a two-sector-two-factor model, a relative price increase in the sector that is relatively intensive in factor X yields a relative cost increase for that factor.[2] For the Chilean case, the mining sector is relatively intensive in high-skilled workers by a very slight margin.[3] Thus, it is likely that my results are not driven by the Stolper-Samuelson effect. Besides, Davidson et al. (1988) show that, for a two-sector-two-factor trade model augmented by search and matching frictions, the Stolper-Samuelson result may not hold when the sector affected by search frictions is sufficiently small.[4] In particular, the mining sector represents -approximately- 5% of the total Chilean employed workers, which implies that it is a relatively small sector.

This evidence motivates the modeling of the commodity sector as a frictional labor market. In this regard, as Dolado et al. (2021) points out:

...to the extent that high-skilled workers may look for better jobs when they land in simple jobs, these jobs become more unstable and more costly for firms to open them. Furthermore, to the extent that high-skilled workers have more stable jobs than less-skilled workers, they are likely to have larger networks helping them to find jobs when unemployed, therefore leading to more efficient search intensity. Finally, it is also plausible that high-skilled workers have larger bargaining power than less-skilled ones since they are more valuable for the firm.

The latter may be specially true in the mining sector, where workers have a high rate of unionization and there exist heterogeneities in unionization rates between high and low-skilled workers within the sector[5], henceforth, this may have an effect in workers' bargaining power. In this regard, workers may

[1]Dynamic Stochastic General Equilibrium for a Small Open Economy

[2]If factors are, as in my framework, high and low-skilled workers, a price increase in the sector that is relatively more intensive in high-skilled workers should increase the high-skilled workers' wage relative to low-skilled workers' wage.

[3]Multiple sources show evidence in line with this claim. First, the 2015 CASEN survey shows that approximately 24% of workers within the mining sector are high-skilled, while high-skilled workers in non-mining sectors are about 23% of the workforce. Also, the CASEN 2013 survey shows similar proportions; about 21% of mining workers are high-skilled, while about 20% of non-mining workers are high-skilled. Another piece of evidence is the one of the *Encuesta Nacional de Empleo* (ENE) survey, which shows that, between 2010 and 2016, the high-skilled workers proportion in mining and non-mining sector was, basically, the same, with 28%. I show a time series plot for the H-skilled rate in both sectors in Appendix A. Finally, the data from the UI registry used for the SVAR analysis displays that the H-skilled rate is 20% for the mining sector and 13% for the non-mining sector.

[4]Aside of this study, there are other papers that argue that the Stolper-Samuelson result does not hold in when some of its assumptions are relaxed. See e.g., Coşar and Suverato (2014) or Goldberg and Pavcnik (2007) for a further discussion.

[5]According to the 2017 CASEN survey, 33,54% of mining workers are unionized, whereas 36.8% of high-skilled workers

anticipate copper price booms and begin collective bargaining processes within each workers union. At this point, it is not clear-cut how each union bargains new wage agreements and, thus, this process may be another source of wage dispersion within the sector. Besides, training costs within the sector[6] may also be an important source of wage variation, since in the mining industry workers have to go through long training periods in order to avoid accidents inside the mines, learn the safety protocols regarding the use of machinery, or related. This may incur in productivity losses depending the time of adaptation of the workers and, also, to additional monetary costs for firms that ask their workers to go through some specific training program. Besides, the process may differ across worker types, depending on how exposed are they to on-the-job hazards.

That being said, the principal contribution of this paper is that it documents a novel empirical fact using administrative data and, to the best of my knowledge, the proposed mechanism that underlies the aforementioned result (labor market institution channel) is new to the literature of effects of commodity price shocks in labor market outcomes.

Besides, I think that Chile provides a good setup to study the heterogeneous effects that commodity (specifically, copper) price shocks may have. First, Chile is the leading copper producer in the world by far, producing an estimated 5.7 billion metric tons of copper in 2020, which represents almost 30% of the global annual copper output. Second, the mining sector's contribution to the Chilean GDP is approximately 10%, and the industry represents about 50% of the country's total exports. These first two points translate into that mining activity and, specially, copper activity has huge participation in the Chilean economic output. In this regard, an economy that is highly exposed to commodity price shocks is a correct place to analyze how do fluctuations in commodity prices affect the heterogeneity in the labor market outcomes of the sector. And third, the Chilean mining sector features three characteristics that may affect labor outcome gaps in non-trivial ways when the copper price fluctuates: (i) highly intensive in low-skilled labor, (ii) high degree of capital-skill complementarity and, (iii) strong labor unions with high levels of worker participation across skill types. These features allow me to set up a structural model with labor market frictions in order to understand how the demand and institutional channel interact.

The reminder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 displays empirical motivation facts for the research question and formalizes them through a SVAR exercise. Section 4 presents the DSGE-SOE model with heterogeneous SAM frictions. Section 5 and 6 do the calibration strategy and the parameter estimation of the model, respectively. Section 7 analyzes the model economy, going deeper in the main mechanisms that drive the results of the model. Section 8 concludes the results of this study and derives policy implications and avenues for further research.

2. Literature Review

This paper is related to four strands of the literature. The first strand analyzes the relation between inequality and natural resource booms which, though limited, highlights significant findings. Bhattacharyya and Williamson (2016) explore how commodity price shocks in Australia increased income

and 30.65% of low-skilled workers are unionized.

[6] As an example, currently the Chilean National Service of Geology and Mining (SERNAGEOMIN) offers two different training programs focusing on different worker types: (i) risk prevention techniques for the national mining industry and, (ii) mining safety monitor. The former targets high-skilled workers (with tertiary education) and the latter targets low-skilled workers. The programs costs are almost $ 3,000,000 Chilean pesos (close to $ 3,300 USD at a exchange rate of 914 $/USD) for the former, and $ 450,000 Chilean pesos (close to $ 490 USD at a exchange rate of 914 $/USD) for the latter.

share for top percentiles in the short run. Similarly, Mohtadi and Castells-Quintana (2021) find diverse impacts on income inequality based on commodity types and initial inequality levels, notably affecting Sub-Saharan Africa and Latin America.

The second strand regards labor market dynamics. Benguria et al. (2018) show how regional commodity price changes can alter skill premiums in Brazil, while Guerra-Salas (2018) presents a theoretical framework explaining declines in skill premiums in Latin America due to commodity price shocks. Pellandra (2015) and Álvarez et al. (2021) analyze the effects of commodity booms on wages, employment, and poverty reduction in Chile, particularly in the mining sector. This paper expands on this strand by incorporating heterogeneity in workers' skills within a dynamic stochastic general equilibrium (DSGE) framework, providing a nuanced understanding of how labor market frictions interact with commodity price shocks to influence employment and wage outcomes in the Chilean mining sector.

Then, this paper aligns with the literature exploring the impact of commodity price shocks on macroeconomic variables, including labor market dynamics. Most studies in this area employ similar methodologies, combining empirical time series evidence with DSGE models augmented by labor market frictions. Naraidoo and Paez-Farrell (2023) demonstrate that commodity price shocks lead to real exchange rate appreciation, output increases, inflation, changes in the nominal interest rate and trade balance, along with a decrease in the unemployment rate. Similarly, Medina et al. (2012) use an SVAR model to analyze terms of trade shocks' effects on the labor market, especially in the mining sector. Guerra-Salas et al. (2021) compare different model specifications and find that the search and matching specification outperforms others in explaining labor market data and macroeconomic variables. This paper extends this literature by incorporating workers' heterogeneity, focusing on how various workers facing different frictions in the labor market respond to commodity price shocks within the commodity sector, particularly in mining, where unique labor market characteristics such as worker movement, unionization, bargaining dynamics, and training costs play significant roles.

Finally, this paper adds depth to the literature embedding the standard Diamond-Mortensen-Pissarides (DMP) framework into a model of the business cycle. Noteworthy works by Hairault (2002) and Campolmi and Faia (2011) have explored the implications of search and matching frictions in open economy models. This study goes further by incorporating workers' heterogeneity within the DMP framework, enhancing the understanding of how commodity price shocks influence labor market outcomes and macroeconomic variables in resource-rich small open economies like Chile.

3. Commodity Price Shocks and Labour Market Outcomes Gap: Empirical Evidence

3.1. Motivation

In order to motivate the discussion, the data shows a pattern regarding the relation between commodity prices against the wage premium and the employment ratio[7]. For the case of Chile, Figure 1 displays the detrended mining sector workers' wage premium and the copper price from the 2005-2019 time span. Series are at a quarterly frequency. In can be seen that, overall, the wage premium increases when the copper price has experienced booms in the business cycle. This is specially true for the commodity

[7] The wage premium is defined as the high-skilled and low-skilled real wage ratio ($\frac{w^h}{w^\ell}$), while the H-to-L employment ratio is defined as the high-skilled and low-skilled employment level ratio ($\frac{H-employment}{L-employment}$). Definitions for high and low-skilled workers are presented in Section 3.

price boom period, which spanned from 2003 to 2011. This evidence suggests that, over the business cycle, the wage premium and the copper price are positively correlated. In fact, the contemporaneous correlation between copper price and wage premium for the time span in Figure 1 is 0.11[8].

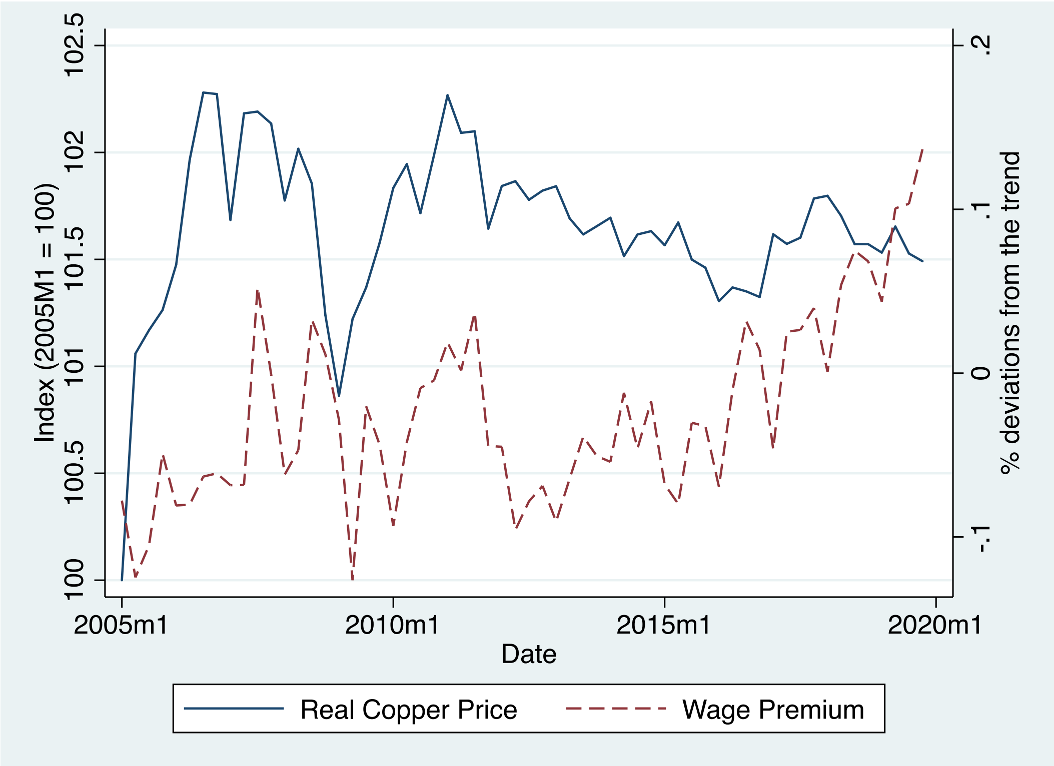


Figure 1: *Copper price index (left) and detrended wage premium (right)*

Source: Chilean Unemployment Benefit database and Central Bank of Chile

Regarding the relation between the employment ratio and the copper price over the business cycle for Chile, Figure 2 shows the detrended mining sector workers' H-to-L employment ratio and the copper price for the 2005-2019 time span[9]. In contrast with Figure 1, it seems that the relation between the employment ratio and the copper price is negative, where in periods when copper price soared, the employment ratio experienced systematic downfalls. Contrary to Figure 1, the correlation between copper price and the employment ratio es -0.44[10].

[8] I also compute $corr(p^{co}_{t-1}, WP_t) = 0.26$, assuming that copper price shocks affect the wage premium with a lag, where p^{co}_{t-1} is the copper price in quarter $t-1$, and WP_t is the wage premium in quarter t.

[9] As was for Figure 1, series are at a quarterly frequency.

[10] Besides, I compute $corr(p^{co}_{t-1}, ER_t) = -0.63$, assuming that copper price shocks affect the H-to-L employment ratio with a lag, where ER_t is the H-to-L employment ratio in quarter t

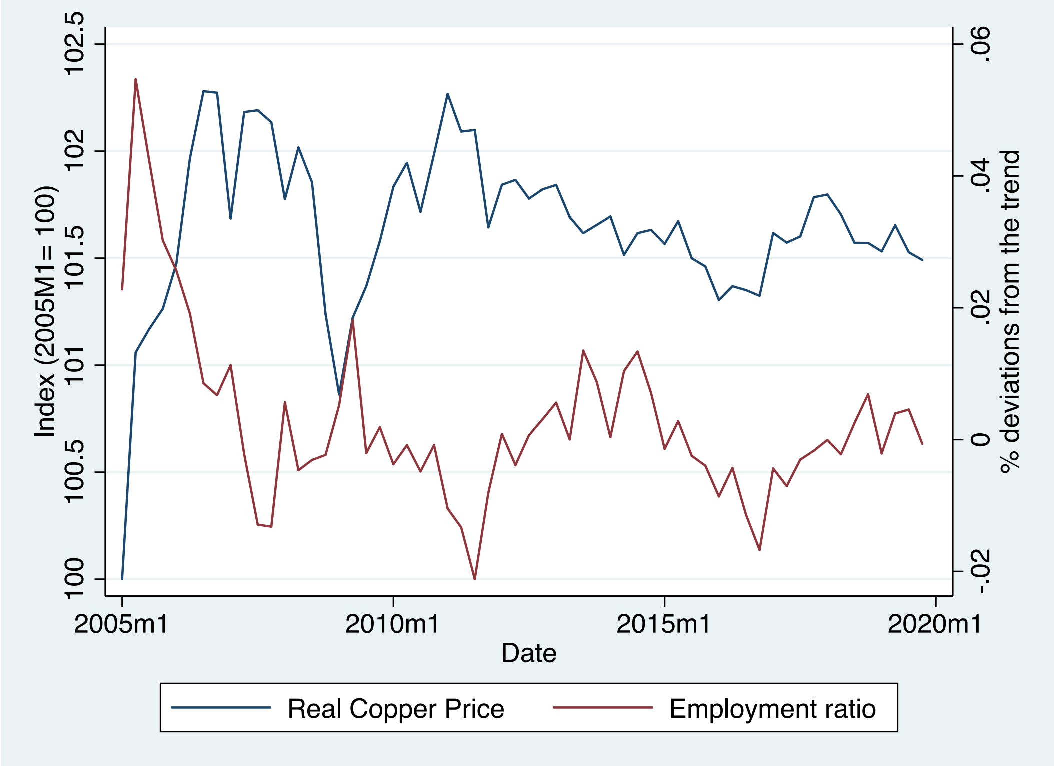


Figure 2: *Copper price index (left) and detrended employment ratio (right)*

Source: Chilean Unemployment Benefit database and Central Bank of Chile

The evidence presented in Figures 1 and 2 is, somewhat, puzzling, because it seems that copper price shocks have different impacts on the employment ratio and wage premium. While, on the one hand, copper price shocks seem to increase the wage premium, on the other happens that copper price shocks decrease the employment ratio. This facts are not consistent with a neoclassical frictionless labor market model, as in Guerra-Salas (2018), Pellandra (2015) and Benguria et al. (2018), in which commodity price shocks affect the wage premium and the employment ratio in the same way through a demand channel.

3.2. SVAR Evidence

In order formalize the latter facts that motivate the research question, I start by identifying the impact of a positive commodity shock on the skill premium and the relative employment rates of high and low skilled workers in a SVAR model. I build time series of both gap using the data of the *Chilean Unemployment Insurance* (UI) which is an administrative database, which has open source material for the 3, 5 and 12% of the whole sample. In this regard, I used the 3% sample, which comprehends 319,425 workers from 2002 to 2020 at a monthly frequency. Labour market data is extracted from this dataset as follows: I calculate wages and employment levels by skill level by obtaining quarterly averages for these variables from 2005:M1-2019M10. Workers are categorized as high or low skilled according to whether they have some college education or not. Specifically, a worker is considered high skilled if he has finished his college education or further, and is considered low skilled if he has incomplete college education or below. On the other hand, employment level is defined as the number of salaried workers in each skill category.[11]

The data is set at a quarterly frequency, covering the sample period between January 2005 to October 2019. I exclude the year 2020 and forth from the sample to exclude the COVID-19 crisis of 2020 which clearly had an effect in several labour market outcomes in the world, not only in Chile. Besides, years 2002, 2003 and 2004 are excluded from the sample because, as Cruz and Rau (2022) argue, the UI system started in October 2002 with new job contracts, so the UI data have become more representative over time. In this regard, Sehnbruch et al. (2015) argue that in 2005 the workers in the UI database represented approximately 50% of all wage earners, reaching 80% of Chilean formal wage earners in 2012. For these reasons, and because the data that I use is a quarterly time-aggregate of the wages of workers over a certain period, which means that dropping years from the sample will leave the sample with less observations to perform the analysis, is that I decided to follow Cruz and Rau (2022) and use the data of the UI base from 2005:M1.

One caveat regarding the UI database is that the observed wages may be truncated by a maximum wage cap that is used as a base for calculation of the monthly amount of the wage proportion that goes to the unemployment insurance savings for every formal worker. Regarding the latter, for the mining sector the UI database records that, since 2005, 20% of the observations are truncated by the wage cap imposed by the administrative entity.[12] This implies that for 80% of mining workers I am able to observe their complete wages, while for the rest I can only observe that they earn a wage that is above the cap, but not the received monthly wage itself. Disaggregating by skill level, there is that 41% and 15% of high and low-skilled workers, respectively, have their wages capped.

The SVAR consists of eight variables: real GDP, the vacancy creation index, the unemployment rate, high-skilled workers real wage rate, the skill premium, high-skilled workers employment rate, the relative employment rate, and real copper price. Following Fornero et al. (2014), I arrange the SVAR into two blocks: (i) a foreign block, and (ii) a domestic block. The only variable in (i) is the real copper price, and the rest variables listed above belong to the domestic block. Here, I assume that foreign variable does not respond to changes in domestic variables. The reduced-form VAR can be written as follows:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \boldsymbol{A}_1 & \boldsymbol{A}_2 \\ \boldsymbol{B}_1 & \boldsymbol{B}_2 \end{bmatrix} \times \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} + \boldsymbol{D} \begin{bmatrix} z_{1,t} \\ z_{2,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix},$$

where $y_{1,t}$ and $y_{2,t}$ are vectors of foreign variables and domestic variables, respectively. Outcomes are explained by previous developments measured by p lags in the variables $y_{1,t-1}, ..., y_{1,t-p}$ and similarly for y_2. Lagged information is gathered in $x_{1,t}$ and $x_{2,t}$. In addition, vector z_t includes deterministic terms such as time trends and constants. The unknown coefficients to be estimated are the elements of the vectors c_1 and c_2 and the matrices $\boldsymbol{A}_1$, $\boldsymbol{A}_2$, $\boldsymbol{B}_1$, $\boldsymbol{B}_2$ and $\boldsymbol{D}$. The error vector is defined by ε_t, where they are expected to by zero on average and their variance-covariance matrix is positive definite.

The VAR is restricted to reflect the small open economy assumption, that is, it is imposed that $\boldsymbol{A}_2 = 0$ such that y_1 forms an exogenous block of variables (which will be subject to the identification scheme that I describe below).

[11] In the literature, the employment level is obtained -in most cases- using the number of salaried workers times the average hours worked in some time span, e.g., a week or a month. I could not use information for hours worked because the UI database does not contain that variable.

[12] The wage cap has increased since 2005. In the early years of the implementation of the UI system the cap was of 90 U.F (Unidades de Fomento), and it has increased systematically to 118.9 U.F in 2019. The U.F is an inflation indexed monetary unit which is used in Chile to set a number of contracts such as e.g., labor, housing, or savings contracts.

Data for real GDP, the vacancy creation index and real copper price were drawn from the Central Bank of Chile's statistics center. Using different information criteria (AIC, HQIC, and BIC) I include one lag of each variable in the VAR.

The strategy that I use here in order to identify real copper price shocks is through a lower triangular Cholesky decomposition. The identifying assumptions are that the copper price affects contemporaneously every variable in the system, while copper price do not react to any impulse in the other variables within a quarter. The ordering of the endogenous variables in the SVAR is as follows: the copper price shock affects GDP, then GDP affects vacancy creation, vacancy creation affects the unemployment rate, then the vacancy creation affects high-skilled employment rate whereas this variable affects the high-skilled real wage rate, and finally this las variable affects the wage premium.

In what follows, I present two different SVAR exercises. First, I only consider labor outcomes for the mining sector. That is, the employment ratio and the skill premium are exclusively considering workers from the mining sector. The latter provides a notion regarding the impact of a positive real copper price shock on workers from a sector that is highly exposed to commodity price fluctuations. The second exercise is leaving aside mining sector workers and, thus, only considering workers from the non-mining sector. Jointly, these exercises let me understand the different impacts that the commodity and non-commodity sectors experience after a commodity (copper, specifically) price shock. That is, I will be able to explore if there is any difference in how the employment ratio and the wage premium react in both sectors.

3.2.1 SVAR for the mining sector

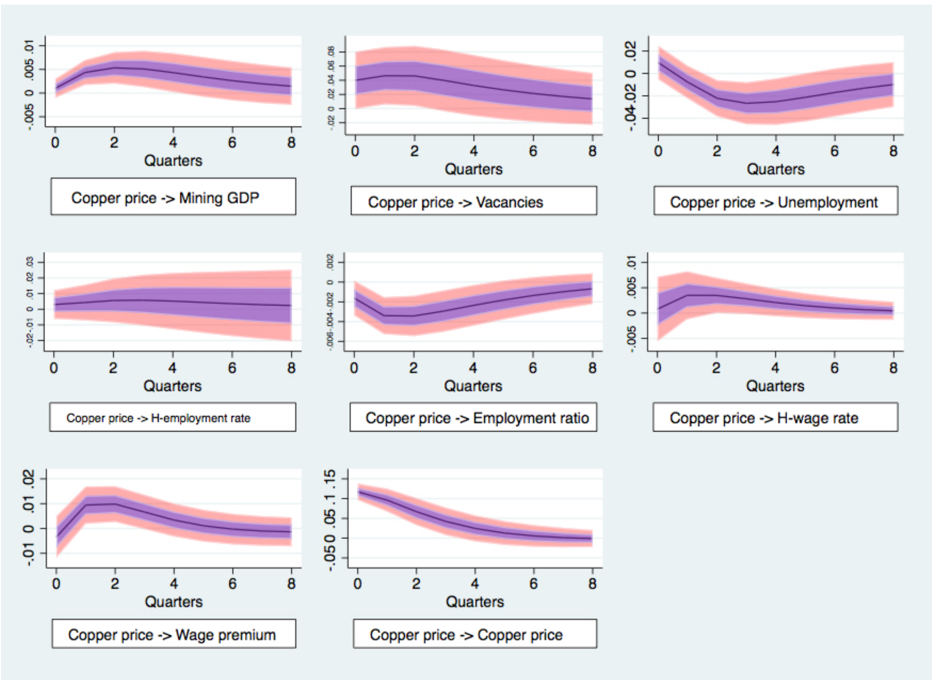


Figure 3: *IRFs to an unexpected increase in the international copper price.*

Notes: The blue and red shaded areas represent the 68 and 90% confidence interval for the SVAR estimation, respectively.

Figure 3 displays point estimates, 68 and 90 percent confidence intervals for the impulse response functions (IRFs) of the baseline SVAR model to the identified real copper price shock. The shock has expansionary effects. After the unexpected copper price increase, total GDP increases persistently. Regarding the labour market variables, the vacancy creation index presents an important increase on impact, returning to its steady state level after, approximately, 10 quarters. On the other hand, the employment ratio decrease significantly on impact and it returns to its steady state level after, approximately, 13 quarters. Finally, the wage premium, despite of its decrease on impact, it increases after the first quarter until the 10th quarter, where it returns to its steady state value.

Overall, the reported IRFs suggest that the gap between high-skilled and low-skilled workers in terms of employment rates is negatively related to an unexpected increase in the copper price, whereas regarding wages the opposite happens. In other words, low-skilled workers are more benefited by an unexpected copper price shock than high-skilled workers regarding their employment level, but high-skilled workers are more benefited by the shock regarding wages. At the peaks of the IRFs, the employment rate decreases by about 3 percentage points, while the wage premium increases by around 5 percentage points. Figure A.1 in the appendix displays the result for this same exercise but using the UI database for the 20% of the whole pool of Chilean mining sector formal workers. The results are qualitatively the same.

The results in this section are comparable with those of Medina et al. (2012), in which they setup an SVAR in order to analyze the response of labor market variables to mining terms-of-trade (TOT). They find that employment in both sectors -tradables and non-tradables-, vacancies and the job creation rate rise upon a TOT shock, whereas the unemployment rate and the job destruction rate decrease after the TOT shock.

3.2.2 SVAR for the non-mining sector

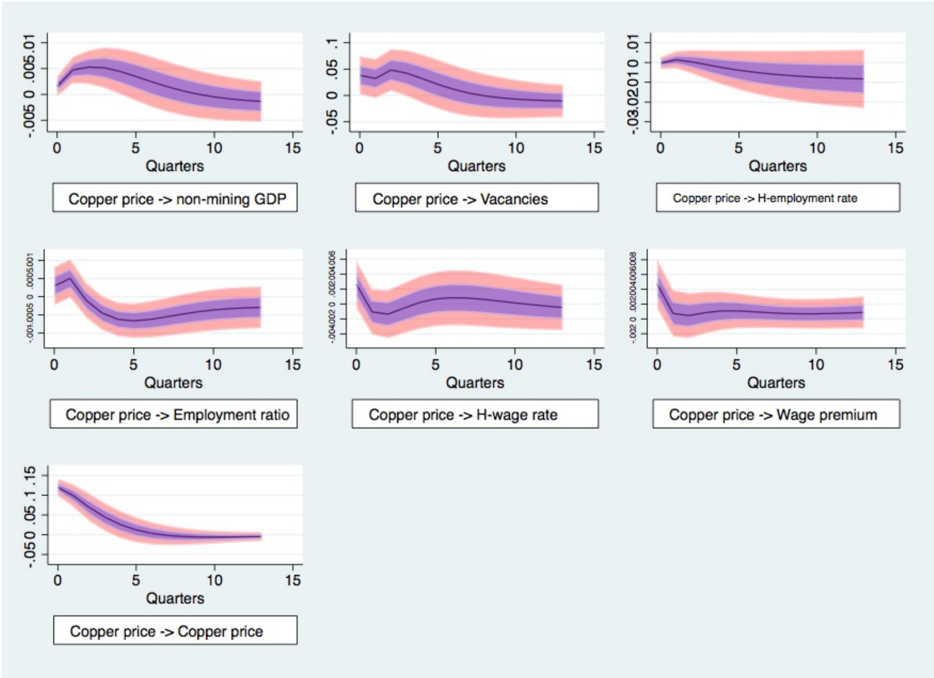


Figure 4: *IRFs to an unexpected increase in the international copper price.*

Notes: The blue and red shaded areas represent the 68 and 90% confidence interval for the SVAR estimation, respectively.

Figure 4 displays point estimates a68 and 90 percent confidence intervals for the impulse response functions (IRFs) of the counterfactual SVAR model to the identified real copper price shock considering labor market variables for workers outside the mining sector. The results are similar with the ones presented in Figure 3; real GDP and vacancies increase as well, but the shock is less persistent, that is, these variables return to their steady-state values faster than for the mining sector, and the effect is only significant during the first 2 or 3 quarters after the impact. Regarding the employment ratio, it decreases as well, getting to a lower bound near of the third quarter after the impact, and returning to its steady-state level approximately after eight quarters. The most remarkable difference between Figures 3 and 4 lies in the wage premium. In the latter, the copper price shock is only statistically significant on-impact and from the first quarter after the shock onwards the wage premium response is not statistically different than 0.

The results in Figure 4 suggest that the effects of a copper price shock outside the mining sector are -qualitatively- similar regarding the employment ratio, but different regarding the wage premium. Here, we can go back to Álvarez et al. (2021) and add that they do not make the difference I make here regarding which subset of workers are included in the analysis. Specifically, they do not condition their analysis on workers that belong -or not- to the commodity (mining) sector. Considering the latter, it is reasonable that the results presented in Figure 4 are similar to those presented in Álvarez et al. (2021), since workers in the mining sector represent about 3% of the total employed workers according to the CASEN survey conducted in 2017.

Summarizing, it seems that a copper price shock decreases the employment ratio inside and outside the mining sector, but it increases the wage premium inside the mining sector and shows mild effects outside it.

With these results in hand, in the next section I present a DSGE-SOE model with SAM frictions in order to rationalize the findings of the SVAR evidence presented above. The novel evidence presented here for the mining sector regarding the negative correlation between the response of the wage premium and the employment ratio to a copper price shock motivates the use of labor market frictions in the structural model, whereas a model without frictions or wage rigidities is only capable to capture the demand effect of a productivity shock.

4. Theoretical Analysis

4.1. The Model

My model belongs to the family of DSGE models with SAM frictions for an small open economy (SOE), which I will refer to as DSGE-SOE. I omitted the New Keynesian feature from the model because my interest is to analyze the impact of commodity price shocks in real variables, and not in nominal variables, therefore nominal rigidities become less relevant in an environment like this. On the other hand, SAM frictions allows me to model unemployment. Workers in the household may work in the commodity sector or in the consumption goods sector. The fraction of commodity sector workers within the representative household is denoted by $x \in (0, 1)$. There is heterogeneity in skills for workers that belong to both, commodity and consumption, sectors. I model this heterogeneity as follows: each household has a fixed proportion of low skilled commodity labor market participants, which may be employed or unemployed. This proportion is called π, therefore there will be that each household has a fixed proportion $(1 - \pi)$ of high-skilled labor market participants. For the consumption good labor market participants, the fixed proportion of low-skilled workers is ω. The latter is depicted in Figure 5.

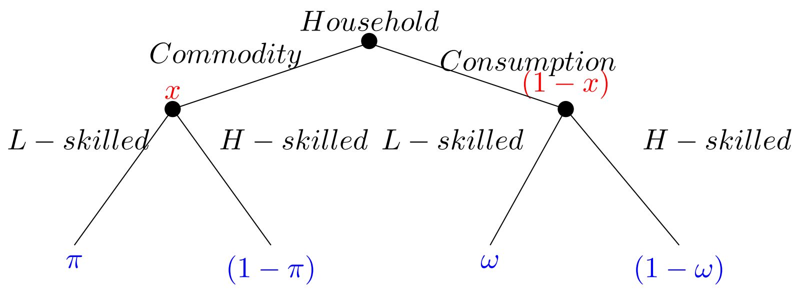


Figure 5: *Representative household allocation of labor between productive sectors.*

For the commodity production market, heterogeneity in skills also imply that workers of different type will face different labor market frictions (*asymmetric* SAM) and in their role in production as well. The latter means that only workers which belong to the commodity sector will face SAM frictions. Also, the representative household has access to the international financial market, where it can buy and sell one-period risk-free foreign bonds.

There is a perfectly competitive firm that produces a homogeneous output by hiring high and low-skilled workers. In order to keep the skill hiring decision tractable, I impose some assumptions on the timing of the events. In the beginning of period t, a job separation shock, δ_t, is realized. Workers who lose their jobs add to the stock of unemployment from the previous period, forming two different pools of job seekers, u_t^h and u_t^ℓ, which denote unemployment for high and low-skilled workers respectively.

Firms create new vacancies for high and low skilled workers, v_t^h and v_t^ℓ, according to a free entry condition. The job seekers match with the vacancies in the labor market, with the number of new matches (m_t^h and m_t^ℓ) determined by a matching technology. Production then takes place in two sectors: (i) commodity sector (constrained by SAM frictions), and (ii) consumption good sector (not constrained by any frictions). Total consumption will be a bundle composed by the consumption good and part of the commodity good. The pool of employed workers at the end of the period is carried over to the next period and the same sequence of economic activities takes place.

4.2. Labor Market Search and Matching in the commodity sector

In the beginning of period t, there are N_{t-1}^h and N_{t-1}^ℓ existing job matches, for high and low-skilled workers respectively. A job separation shock displaces a fraction δ_t of those matches for every worker type, so that the measure of unemployed job seekers by worker type is given by

$$u_t^\ell = \pi x - (1 - \delta_t) N_{t-1}^\ell, \tag{1}$$

and

$$u_t^h = (1 - \pi) x - (1 - \delta_t) N_{t-1}^h \tag{2}$$

where I assume that each worker type in the household has full labor force participation, and the size of the total labor force (high-skilled plus low-skilled workers) is normalized to one.

The job separation rate shock, δ_t, is the same for each worker type, and follows the stationary stochastic process

$$\ln(\delta_t) = (1 - \rho_\delta) \ln(\bar{\delta}) + \rho_\delta \ln(\delta_{t-1}) + \varepsilon_{\delta,t}, \tag{3}$$

where ρ_δ is the persistence parameter and the term $\varepsilon_{\delta,t}$ is an i.i.d normal process with zero mean and a standard deviation of σ_δ. The term $\bar{\delta}$ denotes the steady state rate of job separation.

New job matches are formed between job seekers and open vacancies according to two different sub-markets, one for high-skilled workers and vacancies, and other for low-skilled workers and vacancies. The respective matching functions are

$$m_t^h = \mu_h (u_t^h)^\alpha (v_t^h)^\alpha \tag{4}$$

and

$$m_t^\ell = \mu_\ell (u_t^\ell)^\alpha (v_t^\ell)^\alpha, \tag{5}$$

where μ_h and μ_ℓ are the scale parameters that measures the matching efficiency for high and low-skilled sub-markets, respectively, and $\alpha \in (0, 1)$ is the elasticity of job matches with respect to the number of job seekers, which I keep the same for both sub-markets, to keep things simple.

The flow of new job matches adds to the employment pool, whereas job separations subtract from it. Aggregate high-skilled employment evolves according to the law of motion

$$N_t^h = (1-\delta_t)N_{t-1}^h + m_t^h, \tag{6}$$

whereas aggregate low-skilled employment follows the following law of motion

$$N_t^\ell = (1-\delta_t)N_{t-1}^\ell + m_t^\ell. \tag{7}$$

At the end of period t, searching workers who failed in finding a job match remain unemployed. Thus, high-skilled unemployment is given by

$$U_t^h = (1-\pi)x - N_t^h, \tag{8}$$

and low-skilled unemployment is given by

$$U_t^\ell = \pi x - N_t^\ell. \tag{9}$$

Finally, I define the job finding probability for high-skilled workers as

$$p_t^h = m_t^h / u_t^h, \tag{10}$$

and the job finding probability for low-skilled workers as

$$p_t^\ell = m_t^\ell / u_t^\ell. \tag{11}$$

In similar fashion, the job filling probability for high-skilled vacancies is defined as

$$q_t^h = m_t^h / v_t^h, \tag{12}$$

and the job filling probability for low-skilled vacancies is defined by

$$q_t^\ell = m_t^\ell / v_t^\ell, \tag{13}$$

4.3. The Firms in the commodity sector

A continuum of perfectly competitive firms produce a commodity good Y_t^{co} using high-skilled and low-skilled labor, N_t^k, as inputs. I assume that all firms behave symmetrically and suppress firm-specific indices. Firms choose their desired number of workers, N_t^k, and the number of vacancies, v_t^k, to be posted, by solving the firms's problem, defined by:

$$\begin{gathered}\mathcal{V}(N_t^h, N_t^\ell) = \max_{N_t^h, N_t^\ell, v_t^h, v_t^\ell} p_t^{co} F(N_t^h, N_t^\ell) - \\ \sum_{k \in \{h,\ell\}} (w_t^k N_t^k + \kappa^k v_t^k) + \mathbb{E}_t[\Lambda_{t+1} \mathcal{V}(N_{t+1}^h, N_{t+1}^\ell)]\end{gathered} \tag{14}$$

subject to

$$N_t^k = (1-\delta)N_{t-1}^k + m_{t-1}^k,\ k\ \in \{h, \ell\}, \tag{15}$$

where $\Lambda_{t+1} = \beta\theta_{t+1}(C_{t+1}/C_t)$ is the stochastic discount factor of the households. The real price of the commodity good, p_t^{co} is taken as given by the firm. Posting vacancies has a unit cost of κ^k.
The production function, $F(N_t^h, N_t^\ell)$, is defined by

$$F(N_t^h, N_t^\ell) = Y_t^{co} = Z_t(N_t^h)^{\alpha_h}(N_t^\ell)^{1-\alpha_h}, \tag{16}$$

where Z_t denotes a technology shock, and $\alpha_h \in (0,1)$ is a skill-intensity parameter. The technology shock Z_t follows the stochastic process

$$\ln Z_t = (1-\rho_z)\ln\big(\bar{Z}\big) + \rho_z \ln Z_{t-1} + \varepsilon_{z,t}. \tag{17}$$

The parameter $\rho_z \in (-1,1)$ measures the persistence of the technology shock. The term $\varepsilon_{z,t}$ is an i.i.d normal process with zero mean and finite variance σ_z^2. The term $\bar{Z}$ is the steady state level of the technology shock.

The first-order condition of the firms' problem with respect to v_t^ℓ yields the value function for an open low-skilled vacancy, V_t^ℓ, which satisfies the Bellman equation

$$V_t^\ell = -\kappa_\ell + q_t^\ell \mathbb{E}_t[\Lambda_{t+1}(1-\delta_{t+1})J_{t+1}^\ell + \delta_{t+1})V_{t+1}^\ell]. \tag{18}$$

Analogously, the first-order condition of the firms' problem with respect to v_t^h yields the value function for an open high-skilled vacancy, V_t^h, which satisfies the Bellman equation

$$V_t^h = -\kappa_h + q_t^h \mathbb{E}_t[\Lambda_{t+1}(1-\delta_{t+1})J_{t+1}^h + +\delta_{t+1})V_{t+1}^h]. \tag{19}$$

Equations (18) and (19) capture the fact that since hiring is costly, firms spread employment adjustment over time. Firms that hire workers today reap benefits in the future since lower hiring costs can be expended otherwise. In this sense, equations (18) and (19) link the expected benefit of a vacancy in terms of the marginal value of hiring a worker, J_t^k, to its cost, given by the left-hand side. This is adjusted by the vacancy filling probability, q_t^k. This is, firms are more willing to post vacancies as the higher the probability is that they can find a worker.

On the other hand, the first-order condition of the firms' problem with respect to N_t^ℓ yields the value function for low-skilled employment, J_t^ℓ, which satisfies the Bellman equation

$$J_t^\ell = p_t^{co}\frac{(1-\alpha_h)Y_t^{co}}{N_t^\ell} - w_t^\ell + \mathbb{E}_t\Lambda_{t+1}[\delta_{t+1}V_{t+1}^\ell + (1-\delta_{t+1})J_{t+1}^\ell], \tag{20}$$

Analogously, the first-order condition of the firms' problem with respect to N_t^h yields the value function for high-skilled employment, J_t^h, which satisfies the Bellman equation

$$J_t^h = p_t^{co}\frac{\alpha_h Y_t^{co}}{N_t^h} - w_t^h + \mathbb{E}_t\Lambda_{t+1}[\delta_{t+1}V_{t+1}^h + (1-\delta_{t+1})J_{t+1}^h], \tag{21}$$

Together, equations (18)-(21) and using the standard free-entry condition of search and matching literature, $V_t^k = 0$, yield the job creation condition for high and low-skilled workers, respectively, defined by

$$\frac{\kappa_h}{q_t^h} = \mathbb{E}_t\left[\Lambda_{t+1}(1-\delta_{t+1})\left(p_{t+1}^{co}\frac{\alpha_h Y_{t+1}^{co}}{N_{t+1}^h} - w_{t+1}^h + \frac{\kappa_h}{q_{t+1}^h}\right)\right], \tag{22}$$

and

$$\frac{\kappa_\ell}{q_t^\ell} = \mathbb{E}_t\left[\Lambda_{t+1}(1-\delta_{t+1})\left(p_{t+1}^{co}\frac{(1-\alpha_h) Y_{t+1}^{co}}{N_{t+1}^\ell} - w_{t+1}^\ell + \frac{\kappa_\ell}{q_{t+1}^\ell}\right)\right], \tag{23}$$

The left-hand side captures effective marginal hiring costs, which a firm trades off against the surplus over wage payments it can appropriate and against the benefit of not having to hire someone next period.

4.4. Consumption good sector

The economy has a consumption good sector which produces a good that is consumed by the household domestically. That is, the whole consumption good production is consumed internally. In order to keep things simple, I assume that the consumption good sector labor market is not subject to search frictions, which means that there is full employment in the sector. In other words, as it was stated earlier, if x is the share of household workforce that belong to the commodity sector, then $(1-x)$ is the share of household workforce that belongs to the consumption good sector. Consumption good production depends on the amount of labor employed in that sector, which can be high or low-skilled. For simplicity, I assume that a proportion $\omega \in (0,1)$ of the $(1-x)$ proportion of the population is low-skilled. As there are no search frictions in this sector, the full workforce $(1-x)$ is employed in production activities for the consumption good. Specifically, consumption goods are produced according to the following production function

$$Y_t^c = Z_t(N_t^{c,h})^{\alpha_{c,h}}(N_t^{c,\ell})^{(1-\alpha_{c,h})}, \tag{24}$$

where $N_t^{c,h}$ and $N_t^{c,\ell}$ are the high and low-skilled employed workers in the consumption good sector, and $\alpha_{c,h} \in (0,1)$ is the high-skill intensity in the consumption good production. Besides, I assume that labor in this sector is fixed and exogenously given[13].

One may think of the consumption good sector as a non-tradables sector.

4.5. The Representative Household

The representative household has the utility function[14]

$$\mathbb{E}_t\left[\sum_{t=0}^{\infty}\beta^t\Theta_t(ln(C_t) - \chi^h N_t^h - \chi^\ell N_t^\ell)\right], \tag{25}$$

where $\mathbb{E}[\cdot]$ is an expectation operator, C_t denotes the household consumption, and N_t^k denotes the fraction of k-skilled household members who are employed, where $k = h$ is to denote high-skilled

[13] This assumption comes from the fact that I am only interested in analyzing the labor market dynamics in the commodity sector. Studying, a model that allows for two sectors, endogenous labor and mobility across sectors would be an interesting avenue for future research.

[14] An alternative model assuming GHH preferences was solved in Appendix D. The main results of the benchmark model remain robust to that modification.

members, and $k = \ell$ is to denote low-skilled members. The parameter $\beta \in (0,1)$ denotes the subjective discount factor, and the term Θ_t denotes an exogenous shifter to the subjective discount factor.

The discount factor shock $\theta_t = \frac{\Theta_t}{\Theta_{t-1}}$ follows the stationary stochastic process

$$\ln\theta_t = \rho_\theta \ln\theta_{t-1} + \varepsilon_{\theta,t}, \tag{26}$$

where ρ_θ is the persistence parameter and $\varepsilon_{\theta,t}$ is an i.i.d normal process with zero mean and standard deviation σ_θ^2.

The representative household chooses consumption, C_t, foreign debt, D_t^*, and the fraction of high and low-skilled household members that are employed, in order to maximize the utility function (24) subject to the sequence of budget constraints

$$C_t + D_t^* = r_t D_{t-1}^* + w_t^h N_t^h + w_t^\ell N_t^\ell + \phi(x - N_t^h - N_t^\ell), \forall t \geq 0, \tag{27}$$

where r_t denotes the interest rate that is carried by the foreign debt, and ϕ measures the unemployment benefits, which I assume are the same for high and low-skilled workers within the household.

The interest rate at which the representative household in the small open economy borrows internationally is given by

$$r_t = a + z_t^r + \psi(e^{\hat{D}_t^* - \bar{D}^*} - 1), \tag{28}$$

where a is a constant world interest rate, and $z_t^r + \psi(e^{\hat{D}_t^* - \bar{D}^*} - 1)$ is a country spread over r. The first term of the spread, z_t^r, fluctuates exogenously which follows an AR(1) stochastic process, whereas the second term depends on the average household debt, $\hat{D}_t^*$, which households take as exogenous. As $\hat{D}_t^*$ exceeds its steady state level, $\bar{D}^*$, the interest rate increases. Finally, the parameter $\psi > 0$ governs the sensitivity of the interest rate to deviations of debt from the steady state level. The exogenous term of the spread, z_t^r, follows the following process

$$\ln(z_t^r) = (1 - \rho_{zr})\ln(\bar{z}^r) + \rho_{zr}\ln\left(z_{t-1}^r\right) + \varepsilon_{t,zr}. \tag{29}$$

Denote by $B_t(D_t^*, N_t^h, N_t^\ell)$ the value function for the representative household. The household's problem is to maximize the following Bellman equation

$$B_t(D_t^*, N_t^h, N_t^\ell) = \max_{C_t, N_t^h, N_t^\ell, D_t^*} lnC_t - \chi(N_t^h + N_t^\ell) + \beta\mathbb{E}_t\theta_{t+1}B_{t+1}(D_{t+1}^*, N_{t+1}^h, N_{t+1}^\ell), \tag{30}$$

subject to the budget constraint (27) and the employment laws of motion for high and low skilled workers, (6) and (7). The optimizing decision for employment implies that the employment surplus for type-k workers satisfies the Bellman equation

$$S_t^k = w_t^k - \phi - \frac{\chi^k}{C_t} + \mathbb{E}_t\Lambda_{t+1}(1 - q_{t+1}^k)(1 - \delta_{t+1})S_{t+1}^k. \tag{31}$$

4.6. Nash bargaining wage

When a job match is formed, regardless if it involves a high or a low-skilled worker, the wage is determined by Nash bargaining. The bargaining wage optimally splits the surplus of a job match between the worker and the firm. Let S_t^k denote the type-k worker's employment surplus . The firm surplus is given by $J_t^k - V_t^k$, and it depends on the employed worker's type, $k \in \{h, \ell\}$.
The Nash bargaining problem between a firm and a type-k worker is then given by

$$\max_{w_t^k} (S_t^k)^{b^k} (J_t^k - V_t^k)^{1-b^k}, \tag{32}$$

where $b^k \in (0,1)$ denotes the bargaining power for type-k workers, where I assume that $b^h > b^\ell$.

Solving the problem, the Nash bargaining wage for a type-k worker, w_t^k, satisfies the Bellman equation

$$\frac{b^k}{1-b^k}(J_t^k - V_t^k) = w_t^k - \phi - \frac{\chi^k}{\Lambda_t} + \mathbb{E}_t \Lambda_{t+1}(1-q_{t+1}^k)(1-\delta_{t+1})\frac{b^k}{1-b^k}(J_{t+1}^k - V_{t+1}^k) \tag{33}$$

The closed form solution for wages, w_t^h and w_t^ℓ is given by

$$w_t^h = b^h \underbrace{(p_t^{co}\frac{\alpha_h Y_t^{co}}{N_t^h} + \kappa_h \theta_h)}_{\text{PMg-h + hiring costs}} + (1-b^h) \underbrace{(\phi + \chi^h C_t)}_{\text{Outside option}} \tag{34}$$

and,

$$w_t^\ell = b^\ell \underbrace{(p_t^{co}\frac{(1-\alpha_h) Y_t^{co}}{N_t^\ell} + \kappa_\ell \theta_\ell)}_{\text{PMg-}\ell\text{ + hiring costs}} + (1-b^\ell) \underbrace{(\phi + \chi^\ell C_t)}_{\text{Outside option}} \tag{35}$$

As is typical in models with surplus sharing, the wage is a weighted average of the payments accruing to workers and firms, with each party appropriating a fraction of the other's surplus, that is determined by workers' Nash bargaining power parameter, b^k. The bargained wage also includes hiring costs, which are the mutual compensation for costs incurred by the search process, and the utility cost of working, χ^k. Besides, the bargaining weight, b^k, determines how close the wage is to either the marginal product or to the outside option of the worker, the latter of which has to components, unemployment benefits, ϕ, and the consumption utility of leisure, $\chi^k C_t$.

4.7. Commodity price and production

The commodity supply is given by the commodity production function defined earlier

$$Y_t^{co} = F(N_t^h, N_t^\ell), \tag{36}$$

which describes the commodity production in each period. I assume that a fraction $\gamma \in (0,1)$ of the commodity good is consumed by the households. That is, a fraction γ of the commodity production is consumed by the households, while the remaining fraction, $(1-\gamma)$ is exported. Commodity price is denoted by, p_t^{co}, which is an international price, that is, it is not determined by the commodity producers. This price evolves exogenously by the following AR(1) stochastic process

$$\ln(p_t^{co}) = (1-\rho_{p^{co}})\ln(\bar{p}^{co}) + \rho_{p^{co}}\ln\left(p_{t-1}^{co}\right) + \varepsilon_{t,p^{co}}, \tag{37}$$

where the parameter $\rho_{p^{co}} \in (-1,1)$ measures the persistence of the commodity price shock. The term $\varepsilon_{t,p^{co}}$ is an i.i.d normal process with zero mean and finite variance $\sigma_{p^{co}}^2$. The term $\bar{p}^{co}$ is the steady state level of the commodity price.

Given the latter, commodity profits are defined by the expression $\Pi_t^{co} = p_t^{co}Y_t^{co}$. As it is standard in small open economy models, it is assumed that there is a government which perceives a fraction of the commodity profits. Here I leave that feature aside because the goal is to analyze a direct channel of commodity shock propagation into the labour market outcomes, and not the effect that goes through an increase of the aggregate demand which arises from the positive impact of the commodity price shock in government consumption.

4.8. Government policy

The government finances unemployment benefit payments, ϕ, for unemployed workers through lump-sum taxes. I assume that the government balances the budget in each period such that

$$T_t = \phi(x - N_t^h - N_t^\ell). \tag{38}$$

4.9. Market clearing and search Equilibrium

The trade balance is defined as

$$TB_t = p_t^{co}Y_t^{co}, \tag{39}$$

where it is assumed that the whole commodity production is exported abroad.

Consumption spending has to be equal to consumption good production. That is,

$$C_t = Y_t^c. \tag{40}$$

Goods market clearing requires that consumption spending, vacancy posting costs, and the trade balance add up to the aggregate production. This requirement yields the aggregate resource constraint

$$Y_t = C_t + \sum_{k\in\{h,\ell\}} \kappa_k v_t^k + TB_t. \tag{41}$$

Finally, the net foreign asset position evolves according to

$$D_t^* = r_t D_{t-1}^* + TB_t. \tag{42}$$

5. Parametrization Strategy

The empirical strategy is a mix of both calibrated and estimated parameters. The principal goal when calibrating a subset of parameters is to match steady-state observations and the empirical literature. Afterwards, I estimate the remaining structural parameters and some shock processes in order to fit Chilean time-series data.

5.1. Steady-state and parameter calibration

The model is calibrated using data for Chile at a quarterly frequency. A subset of parameters take values commonly found in the literature for small open economies and DSGE's with SAM frictions, others are calibrated so that the steady state of the model reproduces features for Chile, and the parameters that govern the exogenous processes that drive aggregate fluctuations are estimated using Bayesian techniques, as I will detail in the next section.

The calibrated parameters and targeted steady state values are summarized in Table 1. Going into detail, the unemployment benefit was assumed to be the same between workers' types and equal to 0.25, according to Leduc et al. (2019). Regarding fixed worker shares, first the share of commodity workers in the representative household, x, was calibrated to match the statistics of the 2017 wave of CASEN survey for the share of workers who belong to the mining sector in Chile, which is near of a 5% of the total workforce. Second, the share of low-skilled workers in the economy is, according to the 2017 wave of CASEN survey, approximately 67.6%, which was the value that I used to calibrate the value of π and ω. The elasticity of the matching function, α, is assumed to be the same for high and low-skilled workers, and I took the value estimated for this parameter in Guerra-Salas et al. (2021), that is, $\alpha = 0.516$. Workers' matching efficiency was calibrated in order to capture asymmetric SAM frictions between workers with different skills. They were assumed such that $\mu_h > \mu_\ell$, in line with the evidence in Barnichon and Figura (2015), Wolcott (2021), Eeckhout and Kircher (2018) and Dolado et al. (2021), where the three first aforementioned studies propose a theory of the labor market where firms choose both the size and quality of the workforce, and show that, in a competitive search equilibrium with large firms, high-skilled workers enjoy higher matching probabilities than less-skilled workers. On the other hand, Dolado et al. (2021) calibrates matching efficiencies in order to help the calibration of the remaining parameters; I follow this same approach for these parameters. Regarding the consumption good sector parameters, the skill intensity in consumption good production, $\alpha_{c,h}$, was calibrated following Guerra-Salas (2018), who sets the skill-intensity parameter of the non-tradables production equal to 0.25. Here, I assume that the consumption good sector is similar to a non-tradable sector, since its output is only consumed domestically.

Table 1: *Calibrated parameters*

	Parameter Description	Value	Source
β	Households subjective discount factor	0.9766	Endogenous
ϕ	Unemployment benefit	0.25	Leduc and Liu (2019)
x	Share of commodity workers in the household	5%	CASEN survey
α	Elasticity of matching	0.516	Guerra-Salas et.al (2021)
α_h	Skill-intensity parameter for the commodity production	0.43	Endogenous
$\alpha_{c,h}$	Skill-intensity parameter for the consumption good production	0.25	Guerra-Salas (2018)
μ_h	h-workers matching efficiency	0.62	Barnichon and Figura (2015); Wolcott (2018)
μ_ℓ	ℓ-workers matching efficiency	0.5	Barnichon and Figura (2015); Wolcott (2018)
κ_h	h-vacancies posting cost	0.2	Endogenous
κ_ℓ	ℓ-vacancies posting cost	0.1	Endogenous
$\bar{\delta}$	Mean value for the separation rate	0.08	Jones and Naudon (2009)
π	ℓ-commodity sector workers proportion within the household	0.676	CASEN survey
ω	ℓ-consumption sector workers proportion within the household	0.676	CASEN survey
$U^\ell/\pi x$	ℓ-workers unemployment rate in SS (% of $\ell - workforce$)	0.08	2019 SONAMI report
$U^h/(1-\pi)x$	h-workers unemployment rate in SS (% of h-workforce)	0.08	2019 SONAMI report
χ^h	h-workers disutility from working	0.2856	Endogenous
χ^ℓ	ℓ-workers disutility from working	0.0998	Endogenous
b^h	h-workers Nash bargaining power	0.65	Cahuc et.al (2006), CASEN survey
b^ℓ	ℓ-workers Nash bargaining power	0.58	Cahuc et.al (2006), CASEN survey
$\bar{Z}$	Mean value for the technology shock	1	Leduc and Liu (2019)
$\bar{p}^{co}$	Mean value for the copper price shock	1	-
r	World interest rate (annual)	1%	Guerra-Salas (2018)
$\bar{z}^r$	Annual steady state EMBI spread 2005-2019	1.4%	BCCh
ψ	Risk premium parameter	0.0007	Guerra-Salas (2018)
$\bar{TB}/Y$	Trade Balance-to-GDP ratio	0.03	Endogenous
$\bar{w}_h/\bar{w}_\ell$	Steady State wage premium	1.59	Data
ρ_{zr}	Spread persistence	0.69	Guerra-Salas (2018)
σ_{zr}	std.dev of spread shock	0.17	Guerra-Salas (2018)

Vacancy posting costs are different between high and low-skilled workers. I did not use any calibration of these parameters in the literature because, to the best of my knowledge, there is little evidence on this, and no direct evidence for Chile. Dolado et al. (2021) presents these parameters, but they assume homogeneity in vacancy posting costs for high and low-skilled workers. Despite of the latter, there is evidence that vacancy posting costs vary by skill. Dube and Reich (2010) estimates replacement costs in California are \$2,500 (in 2013 dollars) for blue collar workers and \$8,800 (in 2013 dollars) for professional workers. This includes the cost of recruitment, selection, screening, learning on the job, and separation. Wolcott (2021) takes this evidence and estimates that $\kappa_h = 0.2$ and $\kappa_\ell = 0.1$. Besides, intuitively one may consider that, -generally speaking- as there are less high than low-skilled workers in the economy, the vacancy posting cost of a high-skilled vacancy is higher, because the effort of a firm in finding a high-skilled worker qualified to fill the offered vacancy will be higher as there are less unemployed workers of this type in the economy. Also, having an unfilled high-skilled vacancy may result in higher losses of productivity in comparison with a low-skilled vacancy, since high-skilled workers are supposed to have higher productivity rates. I used the latter reasoning joint with the calibration of α_h, which is the parameter that measures h-workers skill intensity in commodity production, to target the steady state value for the wage premium ($\bar{w}_h/\bar{w}_\ell$) which, according to the data for 2005-2019 in the UI database, is approximately 1.59. Regarding the mean value for the separation shock, $\bar{\delta}$, I follow Jones et al. (2009), who calculate a probability of changing status from employed to unemployed of about 0.04, as well as a probability of changing status from unemployed to employed of about 0.47. These probabilities imply a value for $\bar{\delta}$ of about 7.5%, which is at the lower end of the range of quarterly U.S worker separation rates of 8 to 10% reported by Hall (1995) and the values typically used in the literature (Guerra-Salas et al., 2021).

I target a steady state unemployment rate for both types of workers. This is done by following the SONAMI (Sociedad Nacional de Minería) report, based on the ENE (Encuesta Nacional de Empleo) survey conducted by the National Statistics Institute (INE) in the 4th quarter of 2019. The report states that mining regions in Chile have approximately 7.8% of unemployment on average, where there is little variation amongst different regions. For example, for Antofagasta, which is the mining capital in Chile, the unemployment rate for the period is 7.5%, Atacama has a 7.7% and Coquimbo registers an 8% of unemployment. Based on this information, I decided to calibrate the steady state unemployment rate for both worker types to 8%, which is a higher bound according to the information of the SONAMI report. As I could not disentangle the unemployment rate for different worker types according to their skill (education) level, I assume that the unemployment rate is the same for high and low-skilled workers. Despite the latter, related literature uses that separation rates should differ between workers of different skill levels, where the parameter for high-skilled workers should be lower than that for low-skilled workers (Dolado et al., 2021).

For the Nash bargaining power parameters I used two different -but complementary- criteria in order to do the calibration. First, I look at the related literature (Cahuc et al., 2006); Dolado et al. (2021)) where it is used that the Nash bargaining power parameter for high-skilled workers is higher than that for low-skilled workers. This means that that high-skilled workers perceive a higher share of the surplus that is created by an employment relationship between a firm and a worker, comparing with the share of the surplus that low-skilled workers obtain when bargaining with the firm. While this may be a generalized fact among a wide range of firms and productive sectors, it may not be for a highly unionized economic sector as is mining in Chile. According to the 2017 CASEN survey, 33.54% of mining workers participate in some way in a workers' union, which represents the higher percentage of unionized workers among all economic sectors in Chile. I consider that this fact is important in the wage determination of the mining sector, as bigger workers unions can coordinate pressure activities (as, e.g., strikes) in a better way than smaller ones, which will have an impact in workers' salaries and other working conditions. In addition, I made a descriptive analysis with 2017 wave of CASEN survey and we obtained that 36.8% and 30.65% of high and low-skilled workers[15] belong to a workers union in the mining sector, respectively. These numbers imply that the proportion of high to low skilled workers in a workers' union is close to 48%. This same exercise using the CASEN survey for the year 2015 yields that 34.22% and 32.71% high and low-skilled workers belong to a workers' union, implying that the proportion of high-skilled workers in mining workers' union is a 40%[16]. Summarizing, I calibrate b^k for $k \in \{h, \ell\}$ such that $b^k > 0.5$, which is the standard value in search literature, trying to capture the fact of the high share of unionized workers in the mining sector will imply a higher bargaining power for these workers, and that $b^h > b^\ell$ by a slight margin, trying to capture that union shares between different skilled workers are not so different, and being consistent with the literature mentioned above.

6. Estimation

The parameters that govern the exogenous proceses that act as driving forces of fluctuations in the model economy are estimated using Bayesian techniques. For this purpose, I use HP filtered series of quarterly data and log demeaned for the copper price, the job vacancy index, real GDP and the unemployment rate, which are used as observable variables. Every series was obtained from the Central Bank of Chile Statistics Database. The series time span is from 2005:Q1-2019:Q4. The prior and posterior distributions of the estimated parameters from the model are displayed in Table 2.

The priors are fairly loose, with a Beta distribution with mean 0.5 and standard deviation 0.1 assumed

[15] H-skilled workers were considered to have some college or superior education, while L-skilled workers were assumed to have non superior education.

[16] Looking at the proportions of unionized workers outside the Chilean mining sector we have that for 2015 and 2017 those values were equal to 35% and 39%, respectively.

for coefficients $\rho_{p_{co}}$, ρ_θ, ρ_Z and ρ_δ, and an Inverse Gamma distribution with mean 0.01 and infinite standard deviation for coefficients σ_{co}, σ_θ, σ_Z and σ_δ. The posterior densities are quite different from the priors, which means that the observed variables are informative about the parameters that drive the exogenous processes. Also, there are three parameters associated to the shock processes that were not estimated, which are the persistence of the spread shock, and the standard deviations for the technology and the spread shocks. The reason that I decided not to estimate these parameters was because of identification issues for them conditional to the observed variables that were used for the estimation. Given the latter, these parameters were calibrated according to the information in Table 1.

Table 2: *Estimated Parameters*

		Priors		Posteriors	
	Parameter description	Type	[mean, std]	Mean	90% HPDI
$\rho_{p_{co}}$	Copper price shock persistence	Beta	[0.5, 0.1]	0.9412	[0.9287, 0.9529]
ρ_θ	Preference shock persistence	Beta	[0.5, 0.1]	0.8479	[0.7932, 0.9025]
ρ_Z	Tech.shock persistence	Beta	[0.5, 0.1]	0.9503	[0.9471, 0.9529]
ρ_δ	Job separation shock persistence	Beta	[0.5, 0.1]	0.6912	[0.6028, 0.7835]
σ_{co}	std of copper price shock	Inv.Gamma	[0.01, Inf]	0.1757	[0.1502, 0.2019]
σ_Z	std of tech shock	Inv.Gamma	[0.01, Inf]	0.0839	[0.0715, 0.0952]
σ_θ	std of preference shock	Inv.Gamma	[0.01, Inf]	13.472	[10.7362, 16.1248]
σ_δ	std of job separation shock	Inv.Gamma	[0.01, Inf]	50.8242	[43.4618, 58.3832]

Note: The results are based on 200,000 draws from the posterior distribution using the Metropolis-Hastings (MH) algorithm, dropping the first 100,000 draws in order to achieve convergence. The acceptation rate of the MH algorithm was approximately 30%. HPDI are the highest posterior density intervals. The computations were made using Dynare 4.6.4.

Regarding the model fit, Table 3 displays the comparison between the model simulated and empirical second moments. Specifically, I focus here on comparing the standard deviations, correlations with the copper price process, and serial correlations of the model vis-a-vis the data. Regarding the standard deviation, the simulated series by the model are far more volatile than those of the data. The only exception for the latter is the copper price series, where both, model and data, exhibit similar values for the standard deviation. On the other hand, w_t^h and w_t^ℓ simulated series are in the range of 30 and 60 times more volatile than their data counterparts. Also, is interesting to note that, regarding the model, $Var(w_t^h) > Var(w_t^\ell)$, whereas in the data the opposite happens. This is due to the calibration of the vacancy creation cost, κ_k, for $k \in \{h, \ell\}$. In my benchmark calibration, $\kappa_h = 2\kappa_\ell$. A higher value for the vacancy creation cost, increases the equilibrium value of a workers' wage and also its volatility. In this regard, lowering the calibrated value of κ_h may yield a lower standard deviation for w_t^h and target a $Var(w_t^h)/Var(w_t^\ell)$ rate more in line with the data.[17]. Although, this is at the cost of losing the target value for $\bar{w}_h/\bar{w}_\ell$ displayed in Table 1 Despite of the latter, I perform a re-calibration for κ_h where I decrease its benchmark value from 0.2 to 0.1, which yielded -everything else equal- an h-wage rate standard deviation of 1.24 and a steady-state wage premium of 1.63.

[17]The same can be done increasing the calibrated value for κ_ℓ.

Table 3: *Comparing model and data: second moments*

Statistic	w_t^h	w_t^ℓ	w_t^h/w_t^ℓ	N_t^h/N_t^ℓ	p_t^{co}
Standard deviation					
- Model	2.41	1.76	0.65	0.05	0.23
- Data	0.04	0.06	0.14	0.024	0.31
Correlation with p_t^{co}					
- Model	0.28	0.27	0.3	-0.09	
- Data	0.25	0.05	0.11	-0.46	
Autocorrelation (1st order)					
- Model	0.415	0.407	0.435	0.654	0.69
- Data	0.18	0.46	0.64	0.75	0.71

Regarding correlations with p_t^{co} and serial correlations, the model performs reasonably well. For the former, the model yields a higher correlation with p_t^{co} for h-wages than for ℓ-wages, and the wage premium and the employment ratio correlations with p_t^{co} go in the same direction as the data. For the latter, first order autocorrelation magnitudes are quite similar in the model and data for every variable, with the exception of w_t^h. As the model has the fundamentals of a Small Open Economy, it is of special interest what happens with the serial correlation of the trade balance-to-output ratio. As Garcia-Cicco et al. (2010) mention, models that use a low debt-elasticity of the country premium parameter value exhibit high persistence of consumption which, at the same time, yields a highly persistent trade balance-to-output ratio. In their benchmark case, the trade balance-to-output ratio predicted serial correlation takes values very close to unity, indicating that this ratio behaves as a near random walk. In my case, the serial correlation for the trade balance-to-output behaves quite similar to a stationary process, starting in a value of 0.65 and quickly decreasing the following periods, as Figure A.6 in the appendix displays. This case is very similar to the RBC model augmented by financial frictions in Garcia-Cicco et al. (2010). In this sense, one may think that RBC-SOE models augmented by labor market frictions can also fix the weakness of highly persistent trade balance-to-output ratio and, therefore, it would be interesting to study how a SOE model with labor market and financial frictions interact to match the dynamics of the trade balance. I leave this for further research.

7. Analysis of the Model Economy

Based on the calibrated and estimated parameters, I examine the model's transmission mechanism and its quantitative performance in explaining the dynamics of the model, focusing on labor market dynamics. To help understand the contributions of the shocks and the model's mechanism, Section 6.1 examines impulse response functions of non commodity price dynamics, and forecast error variance decomposition, and Section 6.2 examines the dynamics of a commodity price shock individually, and examine how the shock transmission mechanism works in this case, which is the main focus in order to understand how does this kind of impulse affect labor market gaps between high and low-skilled workers.

7.1. Non-Commodity price dynamics

Figure 6 shows the impulse responses of several macro variables to a positive job separation shock. The shock leads to an increase in unemployment for both types of workers, but low-skilled workers are more affected and, therefore, the employment ratio increases. As the overall employment level goes down, there are less inputs to produce commodity, which provokes a fall in aggregate product and in total consumption. Regarding the wage rates, both wages are negatively affected by the job separation shock but, under my parameterization, high-skilled workers are more affected relatively, which yields a decrease in the wage premium as well. Besides, consistently with Shimer (2005), the job separation shock raises both unemployment and vacancies for both types of worker, which mechanically boosts hiring through the matching function.[18]

Figure 6: IRFs to a shock in ε_δ

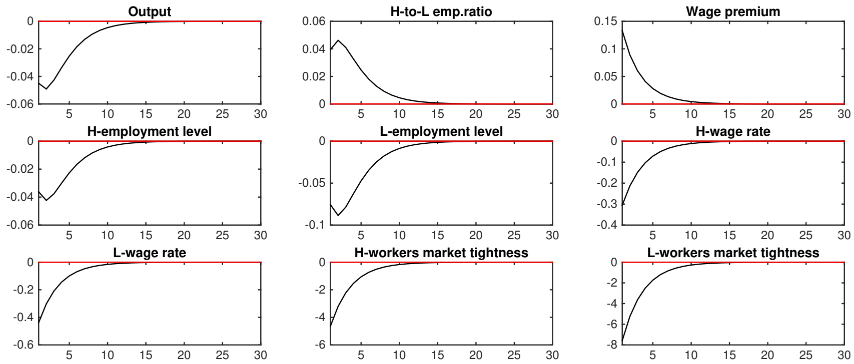


Figure 7 shows the impulse responses to a positive technology shock. The shock leads to an increase in both types of employment, but it is low-skilled labor which benefits the most, which results in a decrease in the employment ratio. As employment levels raise, both aggregate production and consumption raise as well. Wages are positively affected, but high-skilled workers see their wage rate increase the most, which leads to an increase in the wage premium.

Figure 7: IRFs to a shock in ε_z

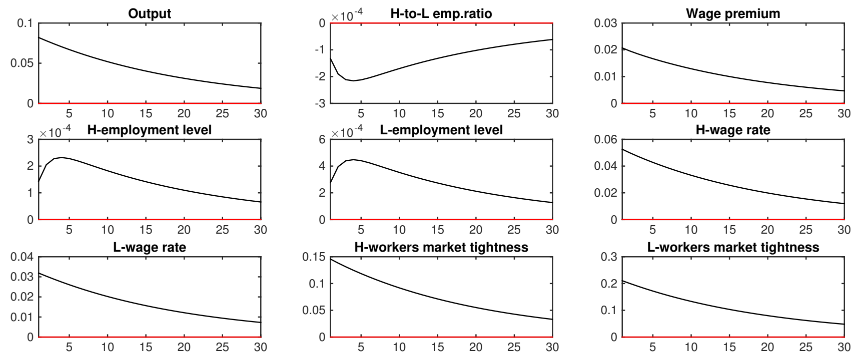
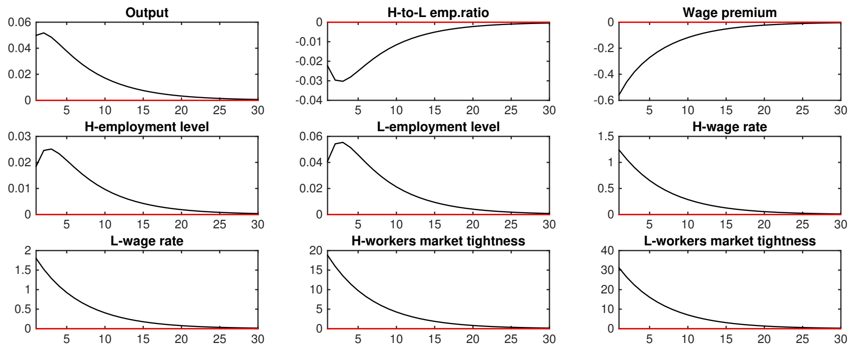


Figure 8 shows the impulse responses to a positive discount factor shock. This shock enters the model through the the job creation condition for both types of workers, leading to a persistent increase on both types of vacancies. As vacancies go up, both employment levels do as well but, under my parameterization, low-skilled workers benefit more by the shock, leading to a decrease in the employment ratio. Again, wage rates for both worker types increase, but high-skilled workers' wages increase more, which yields a higher wage premium.

[18] Shimer (2005) argues that the counterfactual implication of the job separation shock for the correlation between unemployment and vacancies renders the shock unimportant for explaining observed labor market dynamics.

Figure 8: IRFs to a shock in ε_θ



7.2. Variance Decomposition

In this section I explore the relative role of the different shocks that were included in the model to explain movements in key variables. This is done by presenting the unconditional forecast error variance decomposition (FEVD) for a selected set of variables.

Table 4 presents the unconditional variance decomposition of a selected set of key variables in the model, using the posterior means for the parameter values and shock innovation sizes presented in Table 2. Aggregate production is mostly explained by the technology shock, followed by the discount factor shock, and to a lesser extent by the commodity price shock. The simplistic assumption of fixed labor in the production of the consumption good, and the fact that -in the model- this fixed share of workers represents 95% of total workers makes reasonable that the commodity price shock plays not a great role in aggregate production variation. Despite of the latter, commodity price shocks play a modest role in the literature in explaining the fluctuations of GDP (Guerra-Salas et al., 2021).

Because of the size of the standard deviation of the job separation shock, it is to be expected that this shock will be considerably important in the fluctuations of many variables of the model. This is specially true for employment levels for both types of workers, where the job separation shock account for more than 70% of the variation of employment for high and low-skilled workers. This contrasts with Shimer (2005), who argues that, in the U.S, job creation is the main cyclical driver of (un)employment. Nevertheless, Elsby et al. (2013) show that in anglo-saxon economies job separation explains near of the 80% of the unemployment variation, whereas in most european countries job separation and job creation fluctuations explain the same share of unemployment variation. Besides, Jakab and Kónya (2016) find that separation shocks account for two-thirds of the employment variation in their model. My result is, therefore, closer to these evidence than to Shimer (2005).

Table 4: *Forecast Error Variance Decomposition*

Variables	Job separation shock	Technology shock	Discount factor shock	Copper price shock	Interest rate shock
Y	23.81	41.78	34.19	0.22	0
N^h/N^ℓ	69.74	0	30.25	0.01	0
w^h/w^ℓ	5.14	0.27	94.2	0.39	0
N_t^h	74.08	0	25.92	0.01	0
N_t^ℓ	71.81	0	28.19	0.01	0
w_t^h	4.92	0.12	94.76	0.2	0
w_t^ℓ	4.84	0.08	94.94	0.14	0

Note: The numbers reported are the posterior mean contributions (in percentage terms) of each of the four shocks in the estimation to the forecast error variances of the variables listed in each row.

Despite of the latter, the job separation shock explains a little part of the variation of wages, and that of the wage premium, which is consistent with the evidence in Jakab and Kónya (2016) and Guerra-Salas et al. (2021).

Discount factor shocks can directly affect the present values of a job match and an open vacancy, and also the employment surplus for a job seeker (Leduc et al., 2019). Thus, they are important for explaining the the observed labor market fluctuations (Hall, 2017). Quantitatively, the variance decomposition shows that the discount factor shock contributes to about 94% of the variation of wages and the wage premium, on average, and about a 26% of the variation in employment levels.

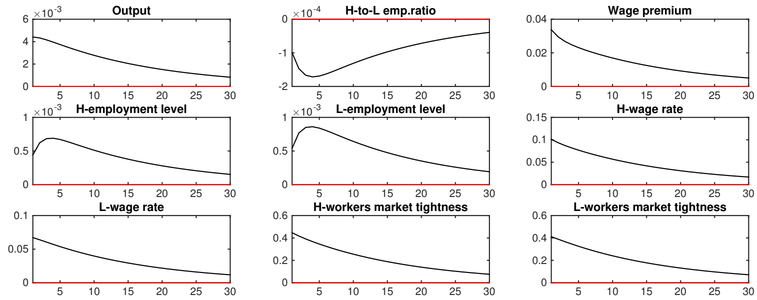
The commodity price shock plays, generally, a modest role in the literature. For example, the commodity price shock in Guerra-Salas (2018) explains 6% of GDP variation, 12% of wage variation, and 6% of employment variation. Here, due to the size of the job separation and discount factor shocks, relatively to the copper price shock, the latter has a negligible part of the variance of most variables of the system. It seems that the copper price shock is most relevant in the output and in the wage premium volatility, but only in a small part.

Finally, the foreign interest rate shock plays almost no role in explaining the variance of the endogenous variables of the model. This is consistent with the evidence of the role of interest rate spread shocks in Guerra-Salas (2018) and Guerra-Salas et al. (2021).

7.3. Positive shock in the commodity price

Figure 9 shows the dynamic effects of a one-standard-deviation shock to the commodity price. The increase in the commodity price leads to an increase in the aggregate demand, which comes from the increase of commodity production, since the raise in the commodity price has no effect in the dynamics of the consumption good. As a share of commodity production is consumed by the households, consumption also increases due to the raise in commodity production. Regarding labor market variables, employment for both types of workers increase due to the commodity price shock. This is because job creation conditions for both types of workers increase and, therefore, firms post more vacancies for high and low-skilled workers, which causes that the job creation raises on impact, causing employment to raise as well. Although, the increase in employment is not homogeneous between skill types. It can be seen from the IRF for the employment rate that the employment for low-skilled workers increases more than the employment for high-skilled workers, which is consistent with the findings in the SVAR exercise in Section 2. Regarding wages, they increase due to the commodity price shock for both types of workers but, this time, those workers who benefit more from the increase of the commodity price are high-skilled workers rather than low-skilled workers. That is, wage rates increase more for high than for low-skilled workers. This can be verified in the IRF for the wage premium, which is positive on impact, and the effect of the commodity price shock vanishes after 10 quarters, approximately.

Figure 9: IRFs to a shock in $\varepsilon_{p^{co}}$.



Comparing the result in Figure 3 with the empirical one in Section 2 we have that my model, qualitatively, reproduces well the dynamics found by the SVAR exercise. Despite of this, I do not try here to match exactly the dynamics showed by the SVAR. This is because I present a rather simple model which has to become more sophisticated in order to match correctly the IRFs in Section 2. Nevertheless, the SVAR results shed light on the intuition that is behind the impact in labor market differences that arise from an exogenous commodity price shock. In this regard, I used the SVAR results to calibrate some structural parameters involving SAM frictions and the skill-intensity in the commodity production, which seem to be appropriate to, at least, replicate qualitatively the empirical evidence.

This result is, somehow, puzzling. Looking into the literature, Guerra-Salas (2018) shows that a positive impact in commodity prices affects the wage premium and the employment ratio in the same way, specifically, he shows that a positive shock in commodity prices causes the wage premium and the employment ratio to fall, which means that low-skilled workers are more benefited by the price shock regarding wages and employment level. The underlying mechanism of this result is that there is an increase in the relative demand of non-tradable goods with respect to tradable goods. As non-tradable goods are more skill-intensive in low-skilled labor there is a crowding-out effect between both labor types, where workers flow from the tradable to the non-tradable sector which, on aggregate, causes the employment ratio to fall. The latter yields that low-skilled wages go up, and that high-skilled wages go down. In the same fashion but studying a different shock, Dolado et al. (2021) show that a monetary expansion shock increases the wage premium and the employment ratio, which means that high-skilled workers are the most benefited by the increase in aggregate demand. Considering this evidence, it seems that exogenous shocks that increase aggregate demand (regardless of the source of the shock) causes that the wage premium and the employment ratio move in the same direction, which is not the case here. This is important particularly when comparing with the evidence in Guerra-Salas (2018), where the source of the shock is the same that I emphasize on here and the results, qualitatively speaking, are not the same.

In order to place my results in the literature I have to describe the source of the increase in the wage gap, on the one hand, and the the source of the decrease in employment level gap, which is not clear yet from the analysis that was made above. That is, I am not able to state which is the transmission channel of the commodity price shock, this is due to the asymmetric SAM frictions and asymmetric skill-intensity in commodity production that I present in the benchmark version of the model. Therefore, in order to separately identify the effects of asymmetric SAM frictions on the one hand, and skill intensity on the other, I build the next four cases to compare with my benchmark: (i) skill-intensity benchmark and re-calibrating SAM frictions, (ii) SAM frictions benchmark and re-calibrating the skill-intensity parameter, (iii) only asymmetric SAM frictions, and (iv) only skill intensity heterogeneity.

Table 5: *Comparative statics for the IRF analysis*

IRF	Parameter change			
	$\downarrow b_h$	$\uparrow \kappa_\ell$	$\uparrow \mu_h$	$\downarrow \alpha_h$
- IRF_{WP}	(-)	(+)	(+)	(-)
- IRF_{ER}	(-)	(+)	(+)	(-)

Note: IRF_{WP} and IRF_{ER} refer to the wage premium IRF and the employment ratio IRF from a commodity price shock, respectively.

Table 5 summarizes the effects regarding the variation of selected model parameters, i.e., those measuring search frictions (b_h, κ_ℓ and μ_h), and the one that governs the skill intensity in commodity production, α_h. Briefly, a decrease in b_h moves downwards both, the IRF_{WP} and the IRF_{ER}; an increase in κ_ℓ and μ_h moves upwards both IRF's, and a decrease in α_h moves downwards both IRF's. The detailed analysis for each case is displayed in the next sub-sections.

7.3.1 Skill-intensity benchmark

Figure C.8 displays the change in the wage premium IRF as H-workers' bargaining power decreases, ceteris paribus. The result is intuitive: the wage premium decreases as H-workers' bargaining power decreases which means, in other words, that as ℓ-workers' relative bargaining power increases, the wage premium will decrease. Also, Figure C.8 shows that a 11% decrease in b^h suffices to have the opposite result regarding the commodity price shock in the wage premium. That is, a 11% decrease in b^h yields that $\partial w_t^h/\partial p_t^{co} < \partial w_t^\ell/\partial p_t^{co}$, thus $\partial WP_t/\partial p_t^{co} < 0$[19]. The wage premium decreases monotonically as b^h decreases.

The other search parameter that is directly related to wages is the vacancy creation cost, κ_k. In order to analyze the wage premium I consider variations in κ_ℓ. The intuition is that as κ_ℓ increases, the wage premium is supposed to decrease. Figure C.9 shows this exercise and it displays that the latter intuition holds. The wage premium decreases monotonically when κ_ℓ increases but at a decreasing rate. The latter implies that even an increase of 300% in κ_ℓ ($100 \times (0.4 - 0.1)/0.1$) can not yield $\partial WP_t/\partial p_t^{co} < 0$. This is telling that the wage premium is more sensitive to variations in b^h than in κ_ℓ.

Even though, regarding the calibration section, I stated that the literature stands for $b^h > b^\ell$ and $\kappa_h > \kappa_\ell$, the latter exercise is useful to have some quantitative approach to understand how much must the search parameters increase (or decrease) in order to produce IRF increasing in the opposite direction with respect to the benchmark. In this case, the decrease in b^h implies a that $b^h - b^\ell = -0.03$, which is a feasible difference in bargaining power between high and low-skilled workers since there is no wide consensus in the literature about the magnitude of this difference. The case for κ_ℓ is more extreme, because I explored up to a 300% increase ($100 \times (0.4 - 0.1)/0.1$) in the parameter, which implies that $\kappa_h/\kappa_\ell = 0.5$. The latter seems less plausible given what was stated in the calibration section regarding that it should be that $\kappa_h > \kappa_\ell$, but it is worth to explore given the quantitative insights that this exercise brings.

[19] $WP_t = w_t^h - w_t^\ell$

The employment ratio is principally affected by two sub-sets of search parameters: μ_k and κ_k, for $k \in \{h, \ell\}$. Figures C.10 and C.11 display the employment ratio comparative statics for μ_h and κ_ℓ, respectively. Figure C.10 shows that the employment ratio increases monotonically when μ_h increases, which is consistent with the basic intuition of the matching elasticity parameter; for a given unemployment and vacancy rates, matching efficiency improvements increase the number of matches. Despite of the latter, qualitatively the result stays the same even with a 45% increase of μ_h with respect to the benchmark, that is, increasing $\mu_h = 0.62$ to $\mu_h = 0.9$.

Finally, Figure C.11 shows that increasing κ_ℓ sufficiently yields that $\partial WP_t/\partial p_t^{co} > 0$. The increase must be 4 times the benchmark value of κ_ℓ for this to happen which, as was stated above, is an unlikely value for this parameter given that it doubles the vacancy posting costs for H-skilled workers. Nevertheless, an increase in κ_ℓ increases monotonically the employment ratio, since it will become relatively cheaper for firms to create H-vacancies with respect to ℓ-vacancies.

7.3.2 SAM frictions benchmark

Figures C.12 and C.13 display the sensitivity of the wage premium and the employment ratio, respectively, with respect to the skill-intensity parameter, α_h. A 31% decrease in α_h (w/r to the benchmark) implies that the wage premium IRF decreases about 4 p.p on impact, and it yields that $\partial WP_t/\partial p_t^{co} < 0$. The latter implies that the benchmark value of $\alpha_h = 0.43$ might be a lower bound for the skill-intensity parameter in my framework, in the sense that a slight decrease would yield a wage premium IRF in the opposite direction with respect to the SVAR analysis. Also, increases of α_h w/r the benchmark value monotonically increases the wage premium, as expected.

Regarding the employment ratio, it increases monotonically with α_h, as expected. Making high-skilled workers more important in the production process triggers more hirings for that type of worker, dampening hirings for ℓ-skilled workers.

As my model does not include capital it is important to consider in the analysis that, as high-skilled workers should have a higher degree of complementarity with capital than low-skilled workers, making α_h higher in my framework should be understood as taking account of the capital-skill complementarity that was not modeled here, therefore, it would be likely that $\alpha_h > 0.43$, which would imply a higher on-impact value for the wage premium and employment ratio IRFs as displayed in figures C.12 and C.13. Of course, the right way to assess this is to include capital-skill complementarity to the present framework.

7.3.3 Only asymmetric SAM frictions

in this section, in order to understand in a better way the transmission mechanism of the model, I suppress the heterogeneity in skill intensity in the commodity production. Doing so allows me to study what is the effect of changing parameters associated with the SAM frictions in my model and analyze its effects in labor market gaps between high and low-skilled workers. That is, I will assume that $\alpha_h = 0.5$, and only focus on variations in the labor market friction parameters of the model, i.e., μ_k, b_k and κ_k, with $k \in \{h, \ell\}$.

A note here, and which is going to be the case for the rest of the section, is that I will only change one labor market parameter corresponding to one skill type or the other. The reason on doing this exercise is that the goal is to explore how do labor market gaps change when the baseline conditions in the labor market change as well. That is, the focus is on increasing the difference in matching efficiency, bargaining power, and vacancy posting costs, among the different workers' skill types.

Figure C.14 shows the IRFs for the employment ratio when the labor market is described by different matching efficiencies. That is, the labor market parameters are the same that are described in Table 1, but I will analyze different IRFs for the employment ratio for the case where μ_ℓ decreases.

From Figure C.14, it can be observed first that the IRF for the employment ratio is still favorable to low-skilled workers when $\alpha_h = 0.5$, and the benchmark calibration for the labor market parameters holds. Nevertheless, the situation changes when I increase the difference in matching efficiencies, $\mu_h - \mu_\ell$. When μ_ℓ decreases from the benchmark value, 0.5, to 0.3 it can be observed that the IRF for the employment ratio now increases. The latter implies that a commodity price shock now favors high-skilled workers employment levels. This increasing trend continues when lowering even more the parameter μ_ℓ to 0.2, where it can be observed that the IRF for the employment ratio increases even more than before because of the commodity price shock. Summarizing, what Figure C.14 displays is consistent with the intuition of standard Search and Matching models that the workers that present less search frictions are those who present higher levels of employment.

Figure C.15 shows the IRFs for the wage premium when the labor market is described by different matching efficiencies, as I did above. In this case, with $\alpha_h = 0.5$, w_h must increase since it is positively related to the skill intensity parameter then, the wage premium for $\alpha_h = 0.5$ will be higher than the one from the benchmark. Besides, it can be observed that when decreasing μ_ℓ the IRFs for the wage premium decrease as well. The intuition for this is explained by the fact that the wage equations present the marginal productivity of k-labor (PMg_k), which is defined by

$$PMg_t^k = \begin{cases} \frac{\alpha_h Y_t^{co}}{N_t^h}, \text{ if } k = h, \\ \\ \frac{(1-\alpha_h) Y_t^{co}}{N_t^\ell}, \text{ if } k = \ell, \end{cases}$$

and when considering $\alpha_h = 0.5$ this expression becomes

$$PMg_t^k = \begin{cases} \frac{Z_t}{2}\left(\frac{HN_t^\ell}{N_t^h}\right)^{1/2}, \text{ if } k = h, \\ \\ \frac{Z_t}{2}\left(\frac{HN_t^h}{N_t^\ell}\right)^{1/2}, \text{ if } k = \ell. \end{cases}$$

The latter expression shows straightforwardly the result of the wage premium IRF decreasing when the matching efficiency for low-skilled workers decreases as well: with a lower μ_ℓ, low-skilled employment (N_t^ℓ) increases less than in the benchmark case. This implies that a commodity price shock will have PMg_t^h increasing less than in the benchmark, and PMg_t^ℓ decreasing less than in the benchmark. This yields that when increasing the asymmetries in matching efficiencies, in particular when decreasing μ_ℓ as I do here, the wage premium will decrease by the effect of the Cobb-Douglas production technology, which provokes that high-skilled wage depends positively on low-skilled employment, and that low-skilled wage depends negatively on its self employment level. Despite of the latter, it is worth mentioning that the effect of decreasing μ_ℓ on the wage premium is considerably low, as Figure C.15 shows.

Now turning to study labour market differences when changing the bargaining power differential between workers' types, Figure C.16 shows how the wage premium is affected when b^h increases above the benchmark value. The blue curve indicates the wage premium dynamics for the benchmark, that is, when $b^h = 0.65$ and internalizing that $\alpha_h = 0.5$. It can be readily seen from Figure C.16 that increasing the high-skilled workers bargaining power increases the wage premium as well. The transmission channel that drives this result is that increasing high-skilled workers bargaining power increases their wage rate and, therefore, a commodity price shock will have a higher impact in w_t^h, which translates in a higher impact into the wage premium.

Figure C.17 shows the employment ratio dynamics when having different high-skilled vacancy posting costs. In particular, in this exercise κ_h increases in order to understand how is the employment ratio affected when high-skilled vacancies are more expensive than in the benchmark case. Again, making high-skilled vacancies more expensive discourages firms to post this kind of vacancies and, thus, they will crowd-out high-skilled vacancies for low-skilled vacancies. In other words, a higher κ_h provokes that firms post less high-skilled vacancies in benefit of posting more low-skilled vacancies. Since the skill intensity in commodity production is the same for both worker types, firms' only care about the relative cost of posting each type of vacancy. Then, as high-skilled vacancies become expensive, firms will be less willing to post that kind of vacancies, which favors low-skilled employment, pushing the employment ratio to go down, as Figure C.17 shows for an increasing κ_h.

7.3.4 Only skill-intensity heterogeneity in commodity production

Now I turn to the case in which there are not SAM asymmetries, so I can focus in how are labor market outcome gaps affected by a commodity price shock when the skill-intensity in commodity production changes. Specifically, I revise the case in which the skill-intensity for high-skilled workers increases. With high-skill intensity in commodity production increasing, basically we say that the elasticity of high-skilled labor in commodity production is higher and then this kind of workers yield more commodity production by unit hired, compared to low-skilled labor. This case can be compared with the skill-intensity for tradable goods mentioned in Guerra-Salas (2018).

Figure C.18 shows the dynamics for the employment ratio when increasing the skill-intensity in commodity production. As the high-skilled elasticity in commodity production increases, firms are more willing to hire high-skilled worker. In other words, the value of high-skilled employment increases as α_h is higher which, at the same time, increases the value of creating a high-skilled vacancy. The latter pushes firms to create high-skilled vacancies and, therefore, high-skilled employment goes up. This result implies that as high-skilled workers become more important in commodity production, they will be more benefited by commodity price shocks than low-skilled workers, which yields a higher employment ratio between workers of different skills.

Finally, Figure C.19 shows the dynamics for the wage premium when increasing the skill-intensity in commodity production and shutting down the SAM frictions heterogeneity. First, it is worth noting that when $\alpha_h = 0.43$ the wage premium response continues to be positive, but less than in the benchmark case because I shutdown the asymmetric SAM frictions. Getting the value of α_h lower, yields a lower response of the wage premium to a commodity price shock. The IRF of the wage premium is negative for $\alpha_h = 0.3$, which it may be due to a Stolper-Samuelson effect, where the skill intensity parameter in the commodity production is the same to the skill intensity parameter in the consumption good sector.

Summarizing, the results of this section are useful to understand better the shock transmission mechanism that underlies in my model. First, analyzing the case that implies only SAM asymmetries we have that increasing the gaps regarding labor market conditions that workers' face by changing the labor market parameters calibration favors the type of worker that faces less frictions, which is consistent with the search and matching literature. In this regard, the only result that is, somewhat, counterintuitive is the one that does the sensitivity analysis of the wage premium when increasing the matching efficiency gap, that is, lowering low-skilled workers matching efficiency. Despite the latter, there is that the wage premium decreases because the particular production technology that I use in the model (Cobb-Douglas), which implies that the marginal productivity for high-skilled workers depends positively in low-skilled labor, and the opposite happens for the marginal productivity for low-skilled workers. It would be interesting to analyze if this result holds or not using another production technology, such as one that presents capital-skill complementarities, for example, but this is out of the scope of this paper.

Regarding the skill-intensity channel in the transmission of the commodity price shock, in Section 7.3.2 I showed that increasing the skill-intensity in commodity production favors high-skilled workers instead of low-skilled workers, that is, the commodity price shock increases labor market differences in terms of employment and wages between different types of workers as commodity production becomes more intensive in high-skilled labor.

7.4. Wealth effects

The commodity price shock increases household's wealth and, as stated in the household's problem, this takes incentives away from supplying labor for both worker types. As worker types exhibit different leisure values is to be expected that this could have important effects in the dynamics of the employment ratio.
In this section, I will briefly check the role of wealth effect as an additional channel that could be driving the results on the employment ratio dynamics, outside of the SAM frictions and the intensity in commodity production.

In my setup, wealth effects can be understood as the differences in value of leisure for both worker types, that is, in the parameters χ^k for $k \in \{h, \ell\}$. In the benchmark analysis, $\chi^h = 0.2856$ and $\chi^\ell = 0.0998$, which means that high skilled labor supply is disproportionally affected. The latter may be explaining at least part of the relative employment fall[20]. In order to assess for the wealth effects on the employment ratio, since both χ^h and χ^ℓ are endogenous, I re-calibrate the SAM parameters, the skill-intensity parameter and the proportion of ℓ-skilled workers in the household so that $\chi^h = \chi^\ell$. As is to be expected, this calibration yields that the IRF's for N_t^h and N_t^ℓ are of the same magnitude and, therefore, the IRF for the employment ratio is 0. Until here, it seems that the wealth effect is crucial in the results displayed in prior sections. Nevertheless, as χ^h and χ^ℓ are functions of SAM parameters and α_h, in order to explore for wealth effects I need to disentangle the value of χ^h and χ^ℓ from the latter parameter set. Thus, I re-calibrate the proportion of ℓ-skilled workers in the household (π), which is outside of the set of SAM and skill-intensity parameter set, to its benchmark value ($\pi = 0.676$) and look at how does the IRF for the employment ratio generated under this calibration compare with the IRF for the employment ratio in the benchmark case. This exercise provides a notion regarding the magnitude of the wealth effects on the employment ratio in my setup as it allows me to check how does the em-

[20] I thank an anonymous referee for pointing this out

ployment ratio IRF respond only to a change in χ^k, isolating the effects of the SAM and skill-intensity parameters on the employment ratio. The result is displayed in Figure C.20.

On impact, when the source of heterogeneities between workers is their proportion on the household, a commodity price shock reduces the employment ratio in about 0.01 p.p, whereas adding heterogeneous SAM frictions and skill-intensity in commodity production reduces the employment ratio in about 0.04 p.p. In other words, the SAM and skill-intensity parameter set enhance the wealth effect almost 4 times regarding the case where these heterogeneities are shutted down.

8. Conclusion

In order to improve our knowledge of the effects that commodity price shocks affect the labor market outcomes of different types of workers and the channels through which these kind of shocks act within the domestic economy, I built a DSGE-SOE model with skill-intensity in commodity production and asymmetric search-and-matching (SAM) frictions in the labor market between high-skilled and low-skilled workers. The model was calibrated and estimated in order to fit Chilean time series for the period 2005-2019. My contribution to the literature is to propose a mechanism that takes into account that workers face SAM frictions and how this interacts with external shocks in a SOE environment, where the commodity production is subject to skill-intensity. My findings show that as skill-intensity in the commodity production falls which -in my environment- means that high-skilled workers become less important in commodity production, labor market gaps decrease as well, but the interaction with SAM frictions, which translates into higher labor market outcomes for the workers face less frictions (high-skilled workers), inhibits the power of the skill intensity to mitigate the wage gap, while it succeeds in decreasing the employment level differences. A highlight here is that I calibrated the model to fit the data for Chile and in this setup happens that, as commodity production is more skill-intensive in low-skilled labor, SAM frictions in favor of high-skilled workers counteract the effect of the skill-intensity effect in commodity production. As Dolado et al. (2021) point out, these findings are not qualitatively specific to commodity price shocks but turn out to be similar for any other type of shocks that increase aggregate demand.

The theoretical model is motivated by a SVAR empirical analysis, in which it is shown that a commodity price shock induces a significant rise in the wage premium, and reduces the employment ratio in the Chilean mining sector. The SVAR analysis shows that employment level differences (measured by the employment ratio between high and low-skilled workers) decreases on impact and this effect is persistent, lasting more than 10 quarters and, regarding the wage gap, it increases on impact and afterwards it tends to decrease, but the positive effect is relatively persistent. This is novel evidence in labor market outcome differences between high and low-skilled workers, using administrative data available in the UI system, which allowed me to handle a considerable amount of worker observations for a relatively long time span, which encompasses the commodity boom period which started in 2002 and lasted to -approximately- 2012, and further. In this regard, extant literature only uses data for the commodity boom period, therefore, I add to these evidence with recent data and covering a longer time span.

Overall, the model reproduces well the findings in the SVAR analysis. Nevertheless, the theoretical model that I propose is simple, and it can be easily extended in a richer New-Keynesian framework, which would allow other channels to act, as the exchange rate channel would do. Also, as in Dolado et al. (2021), my model could be extended allowing that the commodity production to present capital-skill complementarity, which is important in a highly capital-intensive sector as the mining one is. I think these features could be a very interesting avenue to further research.

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A. Tables and plots

A.1. SVAR analysis robustness

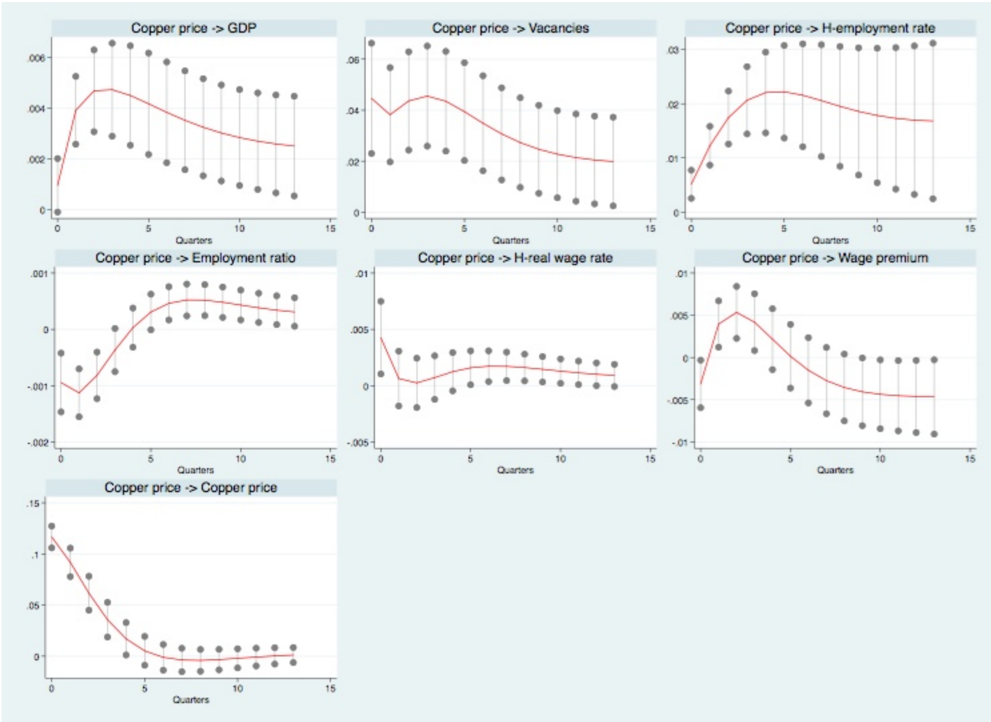


Figure A.1: *IRFs to an unexpected increase in the international copper price*

Note: Calculated using the UI database for the 20% of the whole pool of Chilean mining sector formal workers.

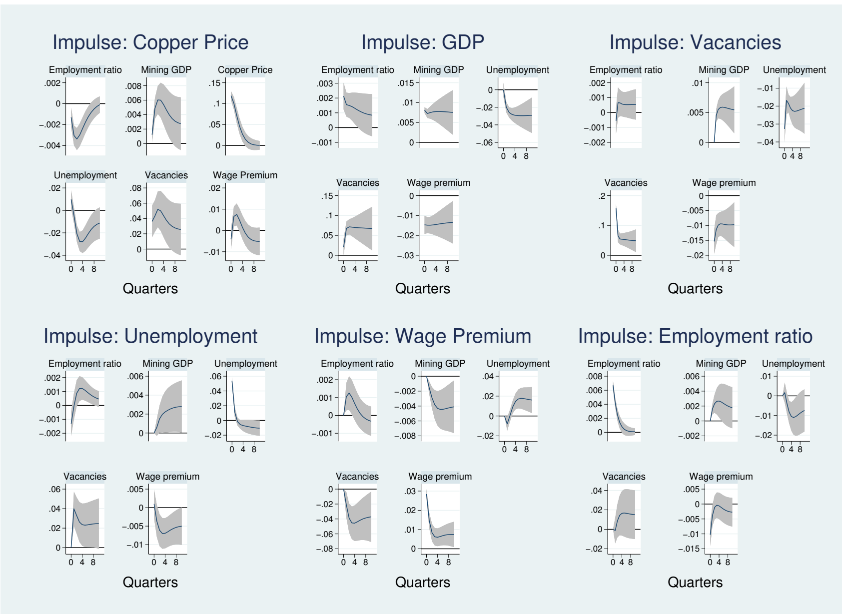


Figure A.2: *IRFs to original ordering including shocks for domestic variables.*

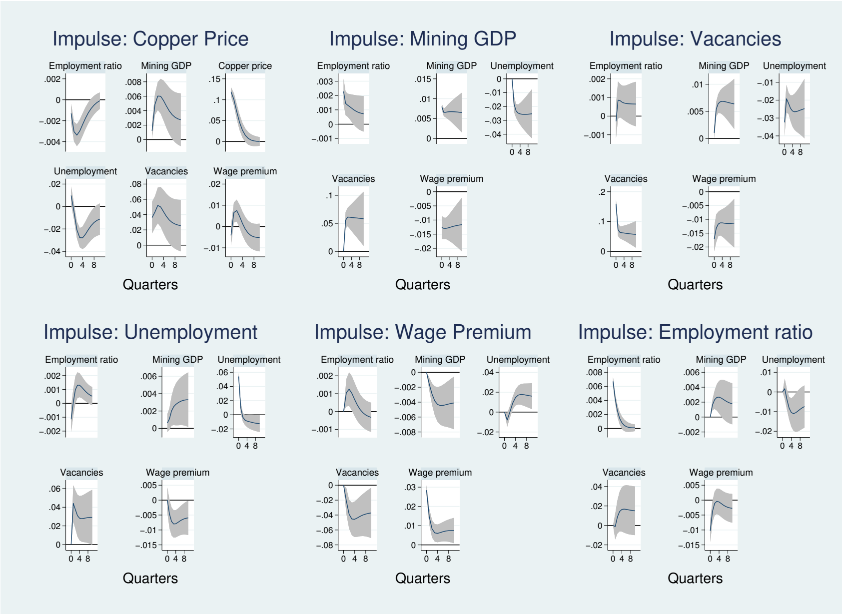


Figure A.3: *IRFs to alternative ordering ($vacancies \rightarrow unemployment \rightarrow GDP \rightarrow emp.ratio \rightarrow wage\ premium$) including shocks for domestic variables.*

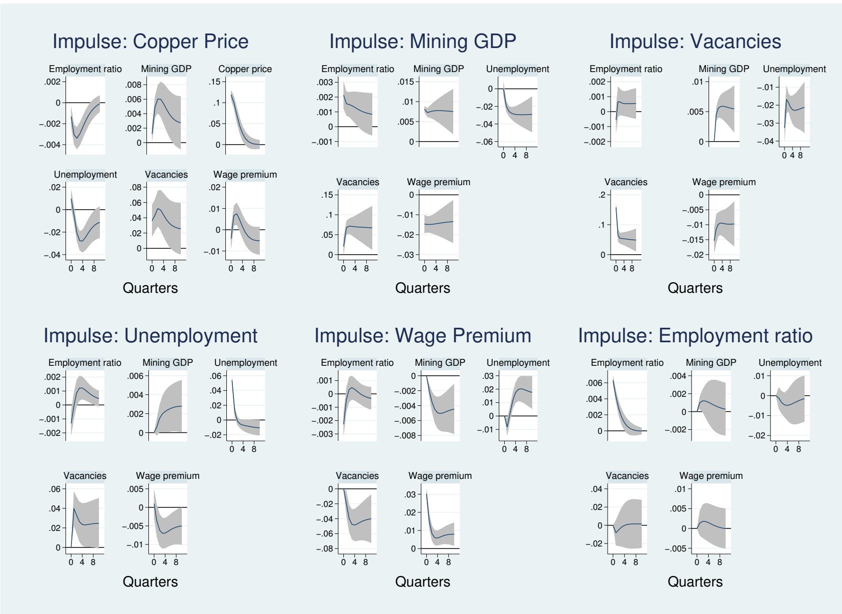
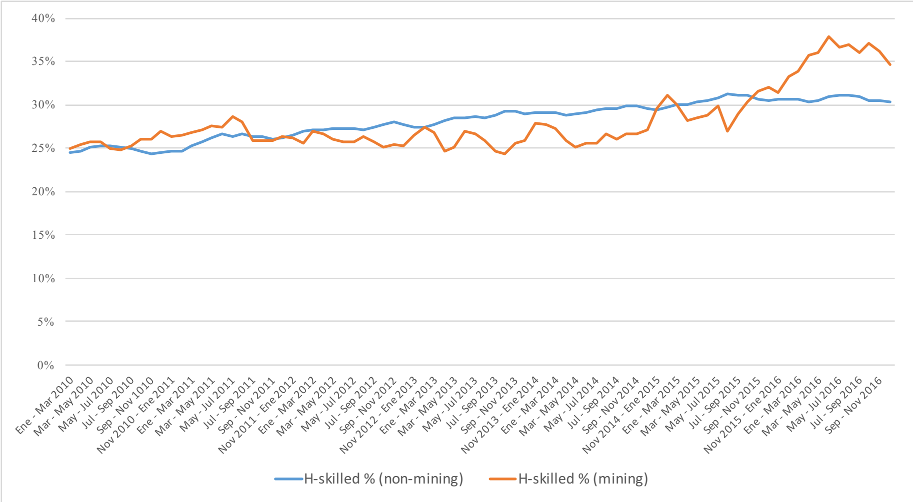


Figure A.4: *IRFs to alternative ordering ($GDP \rightarrow vacancies \rightarrow unemployment \rightarrow wage\ premium \rightarrow emp.ratio$) including shocks for domestic variables*

A.2. Other descriptives



Source: Encuesta Nacional de Empleo (ENE). Instituto Nacional de Estadísticas.

Figure A.5: *H-skilled workers share in mining and non-mining sectors (2010-2016).*

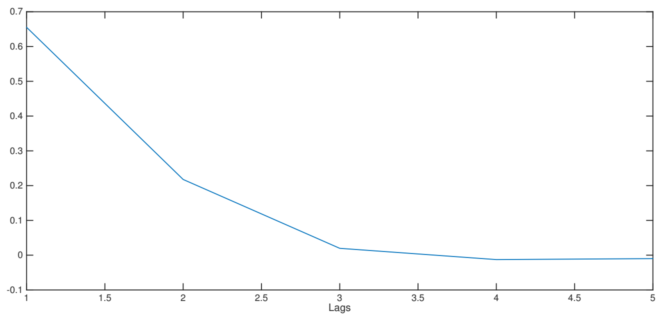


Figure A.6: *The Predicted Autocorrelation Function of the Trade Balance-to-Output Ratio of the DSGE model*

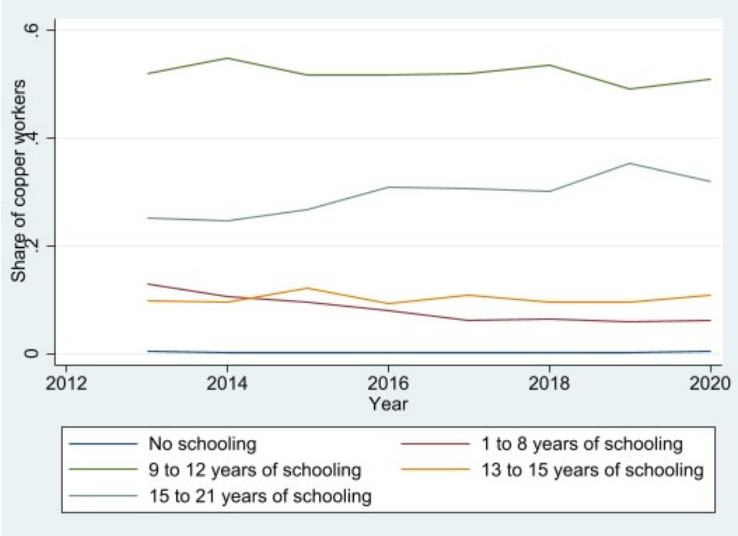


Figure A.7: *Share of Copper Workers en Chile, 2014-2020*

Source: Encuesta Nacional de Empleo (ENE). Instituto Nacional de Estadísticas

B. Equilibrium conditions (non-linear)

$$1 = \beta\,\mathbb{E}_t\left[\theta_{t+1}\,\frac{c_t}{c_{t+1}}\,r_t\right] \tag{43}$$

$$r_t = a + zr_t + \psi\,\left(\exp\left(D_t - D\_ss\right) - 1\right) \tag{44}$$

$$m_t^{\ell} = \left(u_t^{\ell}\right)^{\alpha}\left(v_t^{\ell}\right)^{(1-\alpha)} \tag{45}$$

$$q_t^{\ell} = \frac{m_t^{\ell}}{v_t^{\ell}} \tag{46}$$

$$N_t^{\ell} = m_{t-1}^{\ell} + (1-\delta_t)\;N_{t-1}^{\ell} \tag{47}$$

$$u_t^{\ell} = \pi\,x - (1-\delta_t)\;N_{t-1}^{\ell} \tag{48}$$

$$U_t^{\ell} = \pi\,x - N_t^{\ell} \tag{49}$$

$$m_t^{h} = \mu^{h}\left(u_t^{h}\right)^{\alpha}\left(v_t^{h}\right)^{(1-\alpha)} \tag{50}$$

$$q_t^h = \frac{m_t^h}{v_t^h} \tag{51}$$

$$N_t^h = m_{t-1}^h + (1-\delta_t)\; N_{t-1}^h \tag{52}$$

$$u_t^h = x\;(1-\pi) - (1-\delta_t)\; N_{t-1}^h \tag{53}$$

$$U_t^h = x\;(1-\pi) - N_t^h \tag{54}$$

$$\eta_t^h = \frac{v_t^h}{u_t^h} \tag{55}$$

$$\eta_t^\ell = \frac{v_t^\ell}{u_t^\ell} \tag{56}$$

$$\frac{\kappa_h}{q_t^h} = \beta\,\mathbb{E}_t\!\left[\frac{\theta_{t+1}\,c_t}{c_{t+1}}\;(1-\delta_{t+1})\;\left(\frac{\alpha_h\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N_{t+1}^h} - w_{t+1}^h + \frac{\kappa_h}{q_{t+1}^h}\right)\right] \tag{57}$$

$$\frac{\kappa_\ell}{q_t^\ell} = \beta\,\mathbb{E}_t\!\left[\frac{\theta_{t+1}\,c_t}{c_{t+1}}\;(1-\delta_{t+1})\;\left(\frac{(1-\alpha_h)\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N^\ell{}_{t+1}} - w_{t+1}^\ell + \frac{\kappa_\ell}{q_{t+1}^\ell}\right)\right] \tag{58}$$

$$Y_t^c = Z_t\;(1-x) \tag{59}$$

$$Y_t^{co} = Z_t\,(N_t^h)^{\alpha_h}\,(N_t^\ell)^{1-\alpha_h} \tag{60}$$

$$C_t = Y_t^c + \gamma Y_t^{co} \tag{61}$$

$$Y_t = C_t + v_t^h\,\kappa_h + v_t^\ell\,\kappa_\ell + (1-\gamma)p_t^{co}Y_t^{co} \tag{62}$$

$$w_t^h = b_h\;\left(\frac{\alpha_h\,p_{t+1}^{co}\,Y_{t+1}^{co}}{N_{t+1}^h} + \theta_t^h\,\kappa_h\right) + (1-b_h)\;(\phi + \chi_h C_t) \tag{63}$$

$$w_t^\ell = b_\ell \left(\frac{(1-\alpha_\ell)\, p_{t+1}^{co}\, Y_{t+1}^{co}}{N_{t+1}^\ell} + \theta_t^\ell\, \kappa_\ell \right) + (1-b_\ell)\ (\phi + \chi_\ell C_t) \tag{64}$$

$$\log(\delta_t) = (1-\rho_\delta)\ \log\left(\bar{\delta}\right) + \rho_\delta\ \log(\delta_{t-1}) + \varepsilon_{\delta t} \tag{65}$$

$$\log(Z_t) = (1-\rho_Z)\ \log\left(\bar{Z}\right) + \rho_Z\ \log(Z_{t-1}) + \varepsilon_{t,Z} \tag{66}$$

$$\log(\theta_t) = \rho_\theta\ \log(\theta_{t-1}) + \varepsilon_{\theta,t} \tag{67}$$

$$\log(p_t^{co}) = (1-\rho_{p^{co}}) \log(\bar{p}^{co}) + \rho_{p^{co}} \log\left(p_{t-1}^{co}\right) + \varepsilon_{t,p^{co}}, \tag{68}$$

$$\log(z_t^r) = (1-\rho_{zr}) \log(\bar{z}^r) + \rho_{zr} \log\left(z_{t-1}^r\right) + \varepsilon_{t,zr}. \tag{69}$$

$$emp\_rate_t = N_t^h - N_t^\ell \tag{70}$$

$$wage\_prem_t = w_t^h - w_t^\ell \tag{71}$$

C. IRF's from sections 7.3.1 to 7.3.4

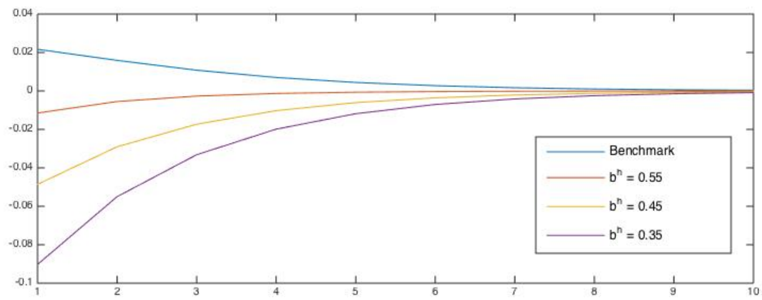


Figure C.8: *Wage premium sensitivity for different b^h and the benchmark skill-intensity, α_h*

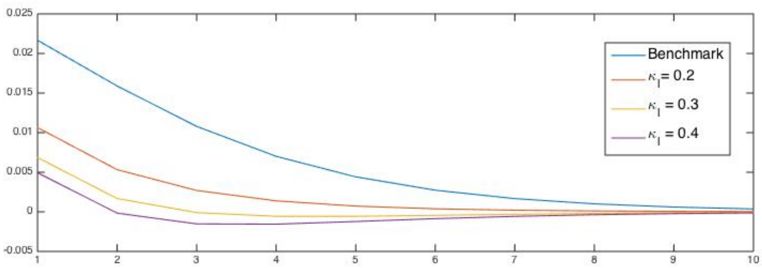


Figure C.9: *Wage premium sensitivity for different κ_ℓ and the benchmark skill-intensity, α_h*

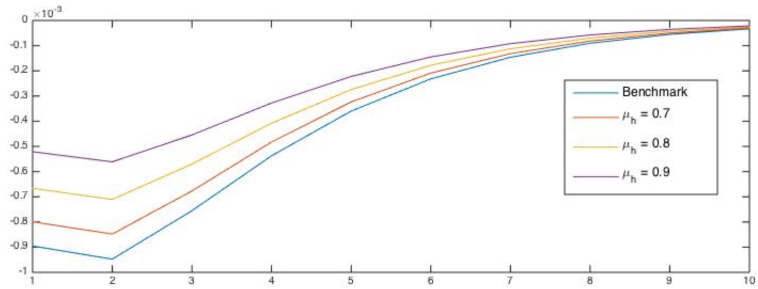


Figure C.10: *Employment ratio sensitivity for different μ_h and the benchmark skill-intensity, α_h*

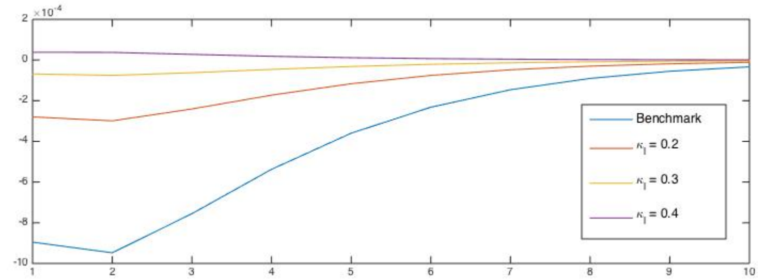


Figure C.11: *Employment ratio sensitivity for different κ_ℓ and the benchmark skill-intensity, α_h*

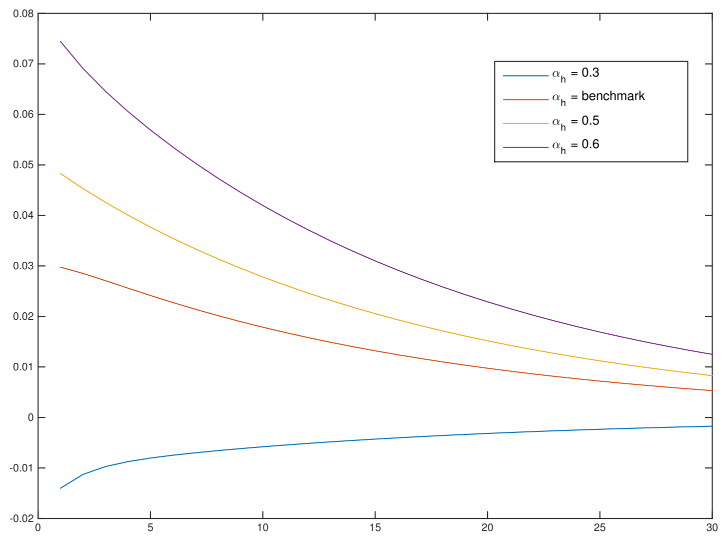


Figure C.12: *Wage premium sensitivity for different α_h and the benchmark SAM friction parameters*

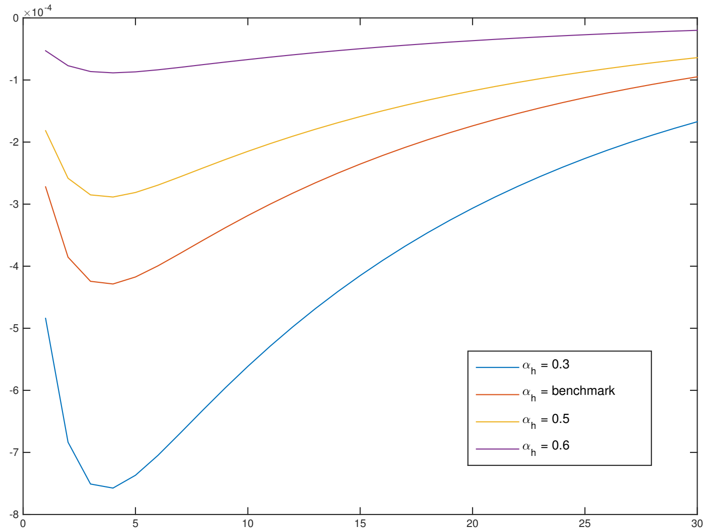


Figure C.13: *Employment ratio sensitivity for different α_h and the benchmark SAM friction parameters*

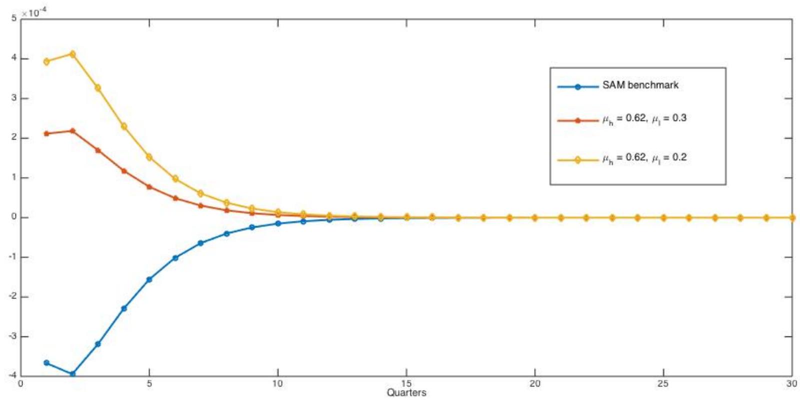


Figure C.14: *IRFs of the employment ratio for different matching efficiencies, μ_ℓ*

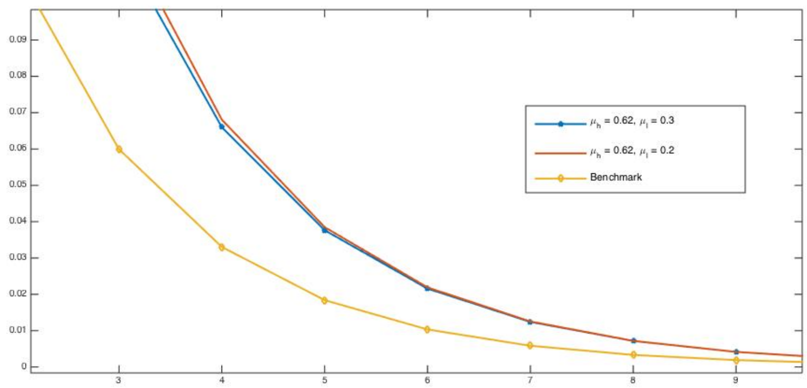


Figure C.15: *IRFs of the wage premium for different matching efficiencies, μ_k*

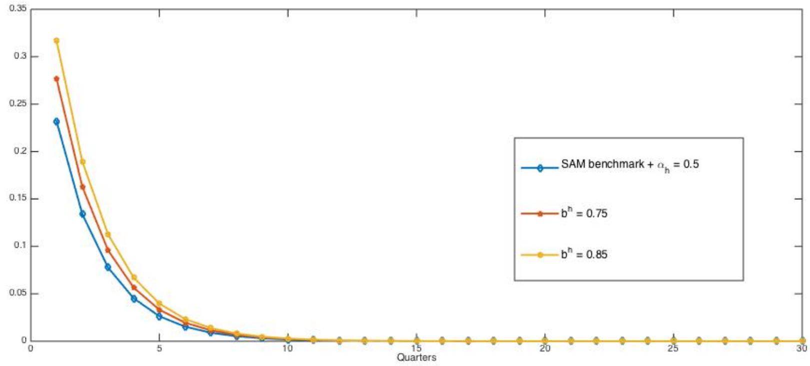


Figure C.16: *IRFs of the wage premium for different H-bargaining power,* b^h

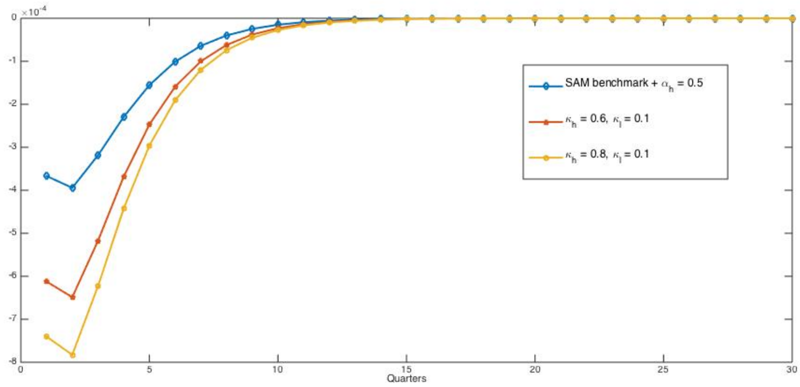


Figure C.17: *IRFs of the employment ratio for different H-vacancy creation cost,* κ_h

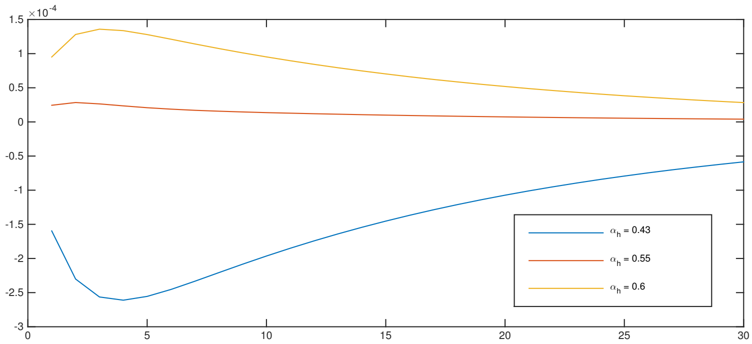


Figure C.18: *IRFs of the employment ratio for different H-skill intensity in commodity production,* α_h

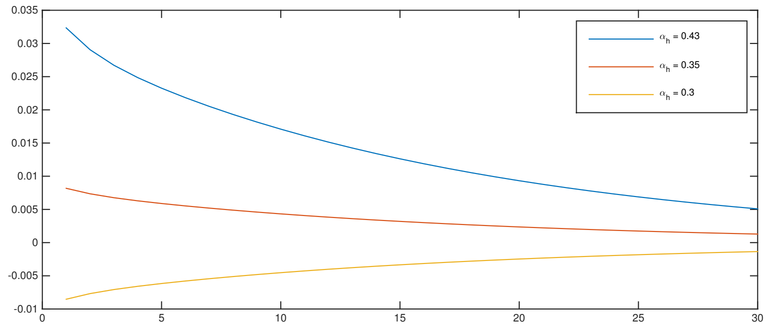


Figure C.19: *IRFs of the wage premium for different H-skill intensity in commodity production,* α_h

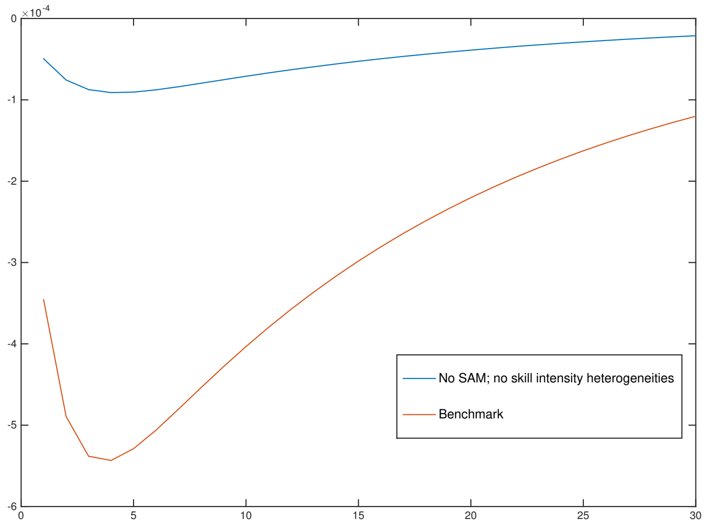


Figure C.20: *IRFs of the employment ratio for different value of leisure,* χ^k

D. DSGE model with GHH preferences

As is standard in international RBC models, this section solves the DSGE-SOE model presented in Section 4.1 but, this time, using alternative household preferences. Specifically, I introduce here the Greenwood, Hercowitz and Huffman (1988) utility function, which is typically referred to as GHH preferences. In this case, the household utility function takes the following functional form

$$U(C_t, N_t^h, N_t^\ell) = \left(C_t - \frac{[\chi^h (N_t^h)^{(1+\phi_1)} + \chi \ell (N_t^\ell)^{(1+\phi_1)}]}{1+\phi_1} \right)^{(1+\sigma_1)}, \tag{72}$$

where ϕ_1 is the labor wage elasticity, which I assume is the same for both types of workers, and σ_1 measures the degree of relative risk aversion.

The main modification for this case with respect to the baseline presented in the main text is in the household optimality conditions, which derive in the closed form solutions for wages. First, the household's problem is to maximize the following Bellman equation

$$G_t(D_t^*, N_t^h, N_t^\ell) = \max_{C_t, N_t^h, N_t^\ell, D_t^*} \left(C_t - \frac{[\chi^h (N_t^h)^{(1+\phi_1)} + \chi \ell (N_t^\ell)^{(1+\phi_1)}]}{1+\phi_1} \right)^{(1+\sigma_1)} + \beta \mathbb{E}_t \theta_{t+1} G_{t+1}(D_{t+1}^*, N_{t+1}^h, N_{t+1}^\ell), \tag{73}$$

subject to the household budget constraint (27) and the employment laws of motion for high and low-skilled workers, (6) and (7). Computing the first order conditions for type-k workers' in problem (73) yield the following optimality condition

$$S_t^k = w_t^k - \phi - \chi^k (1+\sigma_1)(N_t^h + N_t^\ell)^{\phi_1} \left(C_t - \frac{\chi^h (N_t^h)^{(1+\phi_1)} + \chi^\ell (N_t^\ell)^{(1+\phi_1)}}{(1+\phi_1)} \right)^{-\sigma_1} + \mathbb{E}_t \Lambda_{t+1}(1-q_{t+1}^k)(1-\delta_{t+1}). \tag{74}$$

Then, the Nash Bargaining problem between a firm and a type-k worker is given by

$$\max_{w_t^k} (S_t^k)^{b^k} (J_t^k - V_t^k)^{1-b^k}, \tag{75}$$

with which, after a little bit of algebra, I can compute the closed form solutions for wages, w_t^k for $\tilde{z} \in \{h, \ell\}$, given by

$$w_t^k = b^k \left(p_t^{co} \frac{\alpha_k Y_t^{co}}{N_t^k} + \kappa_k \theta_k\right) + (1-b^k) \left[\phi + \chi^k (1-\sigma_1) \left(\sum_{k=h,\ell} N_t^k\right)^{\phi_1} \left(C_t - \frac{\chi^h (N_t^h)^{(1+\phi_1)} + \chi^\ell (N_t^\ell)^{(1+\phi_1)}}{(1+\phi_1)} \right)^{-\sigma_1} \right] \tag{76}$$

This extension was only calibrated, which means that non-structural parameters of Table 2 where parameterized according to the results of the Bayesian estimation in the main text. The new parameters of the utility function, ϕ_1 and σ_1, where calibrated following Uribe and Schmitt-Grohé (2017), where $\sigma_1 = 2$ and $\phi_1 = 0.5$.

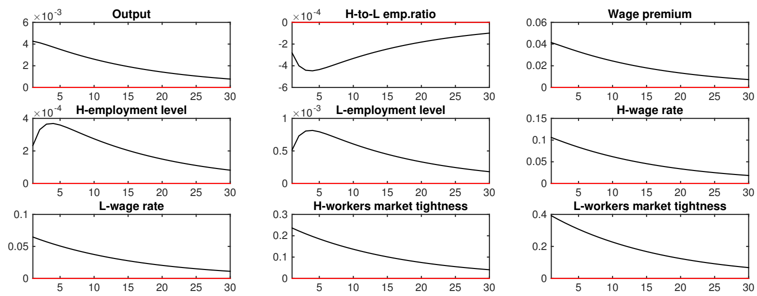


Figure D.21: *IRFs to a shock in $\varepsilon_{p^{co}}$ in the model with GHH preferences.*

E. Wage Decomposition

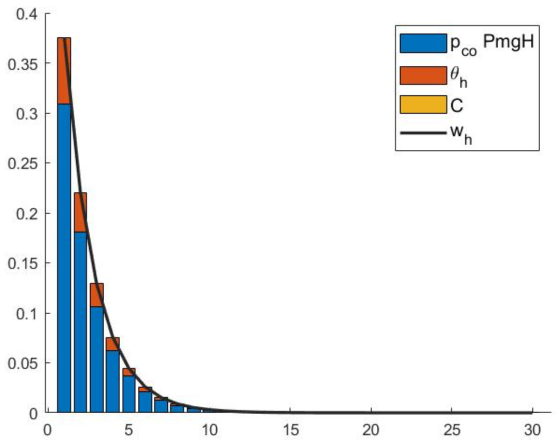
In this section I perform a wage decomposition exercise in order to understand which elements of the workers' wages contribute the most to the wage dynamics when there is a commodity price shock. Let me recall that the wage equation for a k-skilled worker is defined by

$$w_t^k = b^k(p_t^{co} PMg_t^k + \kappa_k \theta_k) + (1 - b^k)(\phi + \chi^k C_t), \text{ for } k \in \{h, \ell\}.$$

Here, we can find three endogenous sources of wage variation that arise from a commodity price shock: (i) Marginal productivity of k-skilled labor, PMg_t^k, (ii) k-skilled labor market tightness, θ_k, and (iii) the household utility of leisure in terms of consumption, $\chi^k C_t$. The commodity price forms part of the wage dynamics as well, but is an exogenous source of variation. Despite of this, I consider in the analysis the joint effect of $p_t^{co} PMg_t^k$ on wage dynamics.

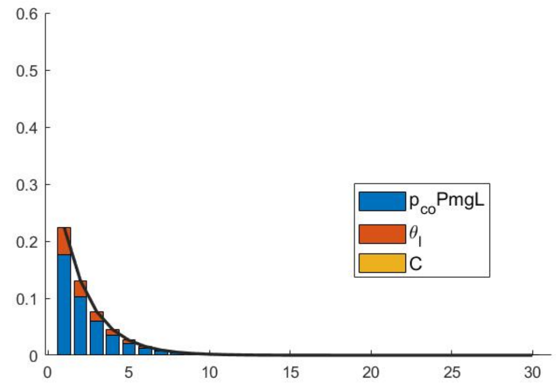
Figures E.22 and E.23 show the wage decomposition by worker skill type. Starting with Figure E.22, it shows the high-skilled workers wage decomposition. It can be seen that the dynamics for w_t^h are mainly decomposed into two components, $p_t^{co} PMg_t^h$ and θ_h. Here, the most important part for the wage variation is attributed to the increase in the marginal productivity of high-skilled labor times the commodity price shock, which accounts for more than the 80% of the variation on impact. The rest of the wage variation is attributed to the increase in the market tightness. The share of variation that comes from the variation in household leisure utility is negligible. These findings are consistent with the evidence showed in Dolado et al. (2021), where it is documented that the wage decomposition dynamics that arise from a monetary shock come from changes in the firm's surplus.

Figure E.22: IRF decomposition for w_t^h



Regarding Figure E.23, it shows the IRF decomposition for low-skilled workers wage rate, w_t^ℓ. The decomposition is quite similar to the one for high-skilled workers, that is, the effect of a commodity price shock in wages is decomposed in, basically, the same two components that explain the variation in wages for high-skilled workers. The difference relies mainly in that, on impact, the share of the variation explained by $p_t^{co} PMg_t^\ell$ is approximately 85%, but the essence of the decomposition is almost the same.

Figure E.23: IRF decomposition for w_t^ℓ



Finally, Figure E.24 shows the decomposition for the wage premium dynamics. Again, as in Figures E.22 and E.23, we have that most of the variation in the wage premium comes from the commodity price impact on aggregate demand pressures. As in Dolado et al. (2021), this suggests that the increase in the wage gap is achieved mostly through changes in the firm's surplus, accounted by $p_t^{co}(PMg_t^h - PMg_t^\ell)$, which lead to adjustments in labor demand. The second factor that contributes noticeably is the difference in labor market tightness, $\theta_h - \theta_\ell$, but by a much lower extent than aggregate demand pressures. In this regard, contrasting with Dolado et al. (2021) I show here that the response in labor market tightness is higher for high-skilled workers than for low-skilled workers. The latter suggests that, for my case, tighter labor markets contribute to increase the wage premium rather to mitigate it, as in Dolado et al. (2021).

Figure E.24: IRF decomposition for the wage premium